

Capital Budgeting and Idiosyncratic Risk

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ABSTRACT

Using an NPV-based revealed-preference strategy, I find that idiosyncratic risk materially affects the discount rate that firms use in their capital budgeting decisions. I exploit quasi-exogenous within-region variation in project-specific idiosyncratic risk and find that, on average, firms inflate their discount rate by 5 percentage points (pp) in response to an 18pp increase in idiosyncratic risk. Moreover, these discount rate adjustments are negatively associated with various measures of firm profitability. I then explore how proxies for costly external financing and agency frictions relate to discount rate adjustments. I find that firms appear to adjust their discount rate upward as a form of risk management when facing costly external financing frictions. Also, I provide evidence that firms partially insure managers against project-specific underperformance to mitigate discount rate adjustments due to agency frictions.

JEL classification: G30, G31, G32.

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One of the most important financial decisions managers face is selecting the best projects among competing investment proposals. Traditional corporate finance theory holds that, when evaluating projects, firms' discount rates should account for the projects' systematic risk, but not their idiosyncratic risk (Bogue and Roll, 1974; Myers and Turnbull, 1977; Constantinides, 1978). Similarly, textbooks warn managers about the temptation of incorporating a “fudge factor” when calculating discount rates in an attempt to compensate for idiosyncratic risk¹, on the grounds that this kind of adjustment can significantly distort the firms' overall allocation of capital. Despite these warnings, surveys conducted by the Association for Financial Professionals (AFP) showed that nearly half of all respondents had manually adjusted their discount rates to account for project-specific risk (Jacobs and Shivdasani, 2012). In surveys, many managers report setting discount rates that are systematically and substantially greater than the cost of capital (Poterba and Summer, 1995; Graham and Harvey, 2001; Graham et al., 2015; Jagannathan et al., 2016). These revelations are worrisome, considering that even small deviations from the *true* discount rate can have sizable effects on managers' decision to pursue a given project. In spite of the focus given to calculating discount rates in managerial training, and the central role it plays in firms' internal allocation of capital, there has been relatively little empirical investigation of managers' actual behavior. This study is among the first to (i) provide causal empirical evidence about how managers adjust their projects' discount rates with respect to idiosyncratic risk, (ii) document the consequences of idiosyncratic risk pricing for firm performance, and (iii) shed light on the economic factors that affect those adjustments.

Measuring firms' discount rates, as well as the level of idiosyncratic risk associated with individual projects, presents significant empirical challenges. First, firms do not report this information. Second, it is not usually possible to observe firms' individual investment decisions. Third, it is generally difficult to compare the investment set across and within firms, limiting researchers' ability to control for confounding factors that might affect the calculation of discount rates. Finally, it is rarely possible to obtain precise estimates of individual projects' expected cash flow.

¹The classical corporate finance textbook of Brealey and Myers (1996) discuss this as follows: “We have defined risk, from the investors viewpoint, as the standard-deviation of portfolio return or the beta of a common stock or other security. But in everyday usage risk simply equals bad outcome. People think of the risks of a project as a list of things that can go wrong. For example: ... A geologist looking for oil worries about the risk of a dry hole. ... Managers often add fudge factors to discount rates to offset worries such as these. This sort of adjustment makes us nervous.”

I overcome these challenges by employing a comprehensive and detailed dataset of onshore vertical gas wells drilled in the United States between 1983 and 2010. Each new well represents a project. Together, the data covers \$53 billion in capital expenditures on 114,969 distinct projects. The dataset has a number of advantages. Specifically, the institutional setting makes it possible to forecast individual projects' cash flows and capital expenditures, and to fully characterize each firm's investment portfolio annually. In addition, the projects are homogeneous and tend to have similar characteristics, which allows meaningful comparisons across projects. For instance, every project in the sample is undertaken using similar drilling technology for which the production function is simple and transparent, meaning that it is possible to easily compute projects' expected monthly production. All projects also produce the same resource, natural gas, further simplifying cross-project comparisons. And finally, the natural gas industry offers an especially rich literature on project-level production forecasting techniques, which means that the dataset is well suited to obtaining plausible estimates of expected cash flow for each project.

First, I provide evidence that, contrary to the recommendations of traditional corporate finance theory, firms inflate their annual discount rates by an average of 3.8 to 6.0 percentage points (pp) in response to a one-standard-deviation increase in projects' idiosyncratic risk. This adjustment is economically meaningful, considering that the average firm in the sample has an estimated weighted average cost of capital (WACC) of 9.6pp. Obtaining this result requires measures of projects' idiosyncratic risk and project-specific discount rates. I measure idiosyncratic risk using a novel method based on the geographic cross-sectional dispersion of projects' idiosyncratic productivity shocks. Specifically, I define each project's idiosyncratic productivity shock as the ratio of the first-year production forecast error over the drilling cost, and then estimate the dispersion of that measure at the regional level every year. I measure discount rates using a revealed-preference strategy based on the net present value (NPV) rule. This process has four steps. First, for each well a firm drills during a given year, I estimate the well's expected cash flows using forecasts of the well's production and natural gas prices. Second, I use those forecasts to compute the project's expected internal rate of return (IRR). Third, I separate all projects within each firm-year subsample into two portfolios depending on whether their level of idiosyncratic risk is above or below the median for that firm-year. And fourth, I estimate the firm's discount rate to be the lowest expected IRR across projects in each of these portfolios. The logic is that the firm's discount

rate must be at least that low, otherwise those marginal projects would not have been undertaken. After assessing wells' idiosyncratic risk and discount rates, I then test the validity of both measures by performing multiple sanity checks. Comparing discount rates across the two firm portfolios, I find a significant relation between discount rates and idiosyncratic risk.

Then, I investigate the consequences of idiosyncratic risk pricing on firms' performance. I introduce a novel measure of idiosyncratic risk pricing to directly test its effects on performance metrics. Precisely, the measure of idiosyncratic risk pricing corresponds to the firm-year discount rate adjustment for a one-unit increase in projects' idiosyncratic risk. I find that for the average firm, a one-standard-deviation increase in the price of idiosyncratic risk is negatively correlated with firms' gross profit margin (-5.1pp), investment rate (-0.8pp), year-over-year asset growth (-0.7pp) and gross profitability (-0.5pp). These results show that adjusting discount rates to account for idiosyncratic risk has important negative consequences.

Finally, I ask *why* managers attempt to account for idiosyncratic risk by adjusting discount rates. Various theories associate managers' motives to adjust their discount rate to external influences (frictions between the firms and the financial market) and to internal ones (frictions between managers and their superiors). It is important to note that the results presented in this final part of the paper correspond to correlations, as I do not have exogenous variation for the costly external financing and agency friction proxies.

With respect to the external frictions theory, Froot et al. (1993) predict that in a world with costly external financing, managers would adjust their discount rates to account for risks that cannot be offloaded to the financial market. That is, they predict that if firms cannot fully diversify their exposure to idiosyncratic risk at the firm level, then they should adjust their discount rates to account for those sources of risk. The authors' logic is that if the firm is hit by a bad idiosyncratic shock, such as drilling multiple bad wells that fail to produce enough cash flows to fund their operations next period, it has two options. The firm can either reduce its investment next period, or turn to the financial market and raise capital, but at a premium because of the costly external financing constraint. Then, managers should take this additional financing cost into account for projects with greater exposure to idiosyncratic risk ex-ante, and adjust their discount rate accordingly. To test this hypothesis empirically, this study builds on Hennessy and Whited (2007) by constructing six proxies of costly external financing and measuring their relation to firms' pricing

of idiosyncratic risk. When using Hennessy and Whited (2007)'s favored proxy of costly external financing, the results are consistent with the prediction made by Froot et al. (1993). Specifically, a one-standard-deviation increase in the cost of external financing is associated with an average increase of 2.3pp in firms' pricing of idiosyncratic risk. Although the results using the other proxies are not always statistically significant, they are mainly directionally consistent with the theoretical prediction.

To examine the role of internal frictions, I relate the pricing of idiosyncratic risk to the size of field managers' budget. A manager with a larger budget is arguably more diversified and therefore faces less total idiosyncratic risk. Simultaneously, Diamond (1984) predicts that risk-averse managers with larger budgets should exhibit a lower idiosyncratic risk premium². In line with Diamond (1984)'s prediction, I find that managers' budget size is strongly related to the pricing of idiosyncratic risk: a one-standard-deviation in firms' average managerial budget size is associated with a 1.16pp reduction in the price of idiosyncratic risk.

To mitigate endogeneity concerns, I use several strategies, including multiple sets of fixed effects and an instrumental variable. With regard to the fixed effect strategy, the nature of the research design makes it possible to control for factors varying at the frequency of the firm-year, because I construct two idiosyncratic risk portfolios per firm-year. For instance, in a given year, a firm may systematically select regions that are riskier, hence the need for a firm-year fixed effect. In addition, I also include an idiosyncratic risk portfolio fixed effect, as there may be a selection effect where some unobserved variables (e.g., managers experience) may systematically be associated to better or riskier regions (i.e., regions with better potential projects, lower risk of bad drilling outcomes). However, the use of those fixed effects does not eliminate the possibility of a within-firm omitted-variable bias. Confounding variation occurring within a given firm-year, such as variation in managers' characteristics may still be correlated with idiosyncratic risk, which is why I also use an instrumental variable. To better illustrate how my instrumental variable strategy solves this problem, I consider two types of within-firm omitted variables: (i) the variables correlated with projects' geographic characteristics, and (ii) variables uncorrelated with projects' geographic characteristics. For instance, field managers overall bargaining power might vary across firms,

²Diamond (1984) highlights that a sufficient condition to obtain this phenomenon is to assume that managers have a DARA utility function. This assumption is relatively general since a large class of models assume that managers have a CRRA utility function, and CRRA utility implies DARA utility.

which could impact how firms assign managers based on their experience to different regions, which corresponds to a source of variation related to (i). Alternatively, the production uncertainty associated with wells drilled by unexperienced managers is higher irrespective of their assigned region, since their ability to properly forecast wells' outcome or operate the drilling equipment is lower than the experienced managers, which corresponds to (ii). In both cases, managers' experience would likely be correlated with projects' riskiness, and thus would be correlated with the overall level of idiosyncratic risk measured for their associated wells' outcomes. Failing to account for the managers' experience would thus lead to a within-firm omitted-variable bias. To deal with this form of omitted variable, it is necessary that the instrumental variable and the fixed effects strategies account for both sources of variation. To address these types of within-firm omitted variables, I use the following instrument for a well's idiosyncratic risk: the largest idiosyncratic productivity shock experienced by any of a firms peers within each township-year³. After controlling for the portfolios' selection effect and the firm-year factors, the information content of peers' idiosyncratic productivity shocks should be uncorrelated with the within-firm omitted variables. Put differently, the instrumental variable assumption in this paper is that the relative level of characteristics of a firms' managers and its peers' managers is randomly distributed within an idiosyncratic risk portfolio. Finally, to satisfy the relevance condition, it is reasonable to assume that the largest idiosyncratic productivity shocks among peer firms would have, on average, a positive relation with the idiosyncratic risk measure, which equals the dispersion of idiosyncratic productivity shocks for each township-year.

The rest of this paper proceeds as follows. Section 1 presents an overview of the literature. Section 2 offers background information on the natural gas industry. Section 3 outlines the data used in the study. Sections 4 to 6 explain the measurement of managers' expectations, firms' discount rates, and projects' idiosyncratic risk, respectively. Section 7 discusses the results and the instrumental variable strategy. Section 8 reports the robustness analysis. Section 9 offers concluding remarks.

³I use the wells' township to determine the wells' respective region. Townships are defined as 6 miles by 6 miles squares of land by the American Public Land Survey System (see Figure 6.1). It is important to note that not all states use the Public Land Survey System. For states not using this system, I construct *synthetic* township, and assign wells to those township using the wells' GPS coordinates.

I. Literature Review

Although there is a robust theoretical and survey-based literature on capital budgeting and project evaluation, this is the first observational study of how managers adjust their discount rates to account for idiosyncratic risk. I summarize in detail the existing literature addressing each of the paper's three core contributions, as I introduced them in the previous section.

First, by showing that firms appear to price idiosyncratic risk, this study provides direct empirical backing for the discussions of capital budgeting (e.g., Poterba and Summer (1995), Graham and Harvey (2001), Graham et al. (2015), and Jagannathan et al. (2016)). Those survey-based papers document and discuss the existence of a puzzling gap between firms' estimated weighted cost of capital (WACC) and the discount rates reported in their surveys. The present study provides a direct causal estimate based on firms' actual choices, of how idiosyncratic risk affects discount rates. In doing so, this paper also contributes to the theoretical literature providing guidance on the proper way to compute discount rates (e.g., Bogue and Roll (1974), Myers and Turnbull (1977), and Constantinides (1978)). This paper establishes both that managers appear to include a project-level idiosyncratic risk premium in the calculation of discount rates, and that doing so has adverse consequences on performance.

Second, my paper also relates to Kruger et al. (2015) who document a different mistake firms make when computing discount rates. Kruger et al. (2015) show that a firm often applies a unique discount rate to its projects, even when projects face different levels of systematic risk. While Kruger et al. (2015) show that firms adjust their discount rate too little, I find they adjust too much. Also, when Kruger et al. (2015) focus on systematic risk, I focus on idiosyncratic risk. The two papers show that these distinct mistakes both have adverse effects on firms' performance.

Third, this paper contributes to the literature studying the effect of idiosyncratic risk on firms' behaviors. Panousi and Papanikolaou (2012) point out that firms reduce their overall level of investment when their firm-level exposure to idiosyncratic risk increases, which is plausibly suboptimal from the standpoint of a well-diversified investor. The authors identify managers' remuneration and ownership structure as important factors to rationalize the observed phenomenon. My paper relates to Panousi and Papanikolaou (2012)'s main contribution by providing direct evidence as to which capital-budgeting lever is altered by managers when taking into account project-level idiosyncratic

risk: the discount rate. At the same time, I identify additional attributes of the firm that appear to be relevant in understanding why idiosyncratic risk is accounted for in the discount rate, enriching our comprehension of firms' response to idiosyncratic risk. Also, my results suggest not only that the overall level of idiosyncratic risk experienced at the firm level matters, but that the exposure of specific local managers to project-level idiosyncratic risk can ultimately have firm-wide impacts. Finally, my setting enables me to directly relate the intensity at which firms price idiosyncratic risk to negative performance outcomes, such as lower gross profit margins.

Fourth, this study also contributes to the extensive literature on the effects of costly external financing on firms' choices⁴. Most directly related to this paper is Froot et al. (1993), who study how costly external finance affects the relation between capital budgeting and risk management. The authors predict that firms facing costly external financing should adjust their discount rates to account for risks that cannot be hedged or diversified. Supporting this view, I find that firms facing high costs of external finance do in fact adjust their discount rate to manage risk.

In addition to these research areas, there are other strands of literature that address how corporate policies and the characteristics of firms affect managers' risk tolerance. Two prior findings are especially relevant. The first of these is that compensation contracts play a significant role in mitigating risk tolerance misalignment between managers and their superiors (Ross, 1973; Holmstrom and Weiss, 1985; Lambert, 1986). A rich empirical literature indicates that market-based compensation contracts affect managers' risk tolerance (Agrawal and Mandelker, 1987; Tufano, 1996; Guay, 1999; Rajgopal and Shevlin, 2002; Coles et al., 2006; Armstrong and Vashishtha, 2012; Gormley et al., 2013), while theoretical work suggests that such contracts can shift managers' focus from maximizing long-term value to pursuing short-term benefits (Narayanan, 1985; Bolton et al., 2006). Similarly, empirical findings show that market-based compensation can induce excessive risk taking in managers (Bebchuk and Spamann, 2010; Dong et al., 2010; Hagendorff and Vallas-cas, 2011). Overall, these results suggest that owners solely using wage contracts to align their managers' decisions with their preferences might also subject their firms to potential drawbacks. Of greater immediate relevance, Holmstrom and Costa (1986) provide a theoretical argument suggesting that capital budgeting policies can be used to complement compensation contracts in order

⁴This literature extends at least back to Miller and Orr (1966). Notable contributions include Fazzari and Petersen (1993), Hennessy and Whited (2007), Lyandres (2007), and Bolton et al. (2011), among others.

to more successfully align managers' decisions with those of their supervisors. The present study contributes to this literature by empirically identifying the size of managers' budgets as a tool to alter risk tolerance. Specifically, the findings reported here suggest that it is possible to increase the idiosyncratic risk tolerance of a manager by increasing the size of his allocated budget, in line with the diversification effect proposed by Diamond (1984).

II. Natural Gas Industry: Institutional Background

A. *Project Overview: The Drilling Technology*

Two prominent technologies exist to drill natural gas wells: vertical drilling and horizontal drilling (see Figure 1). In this paper, I focus specifically on vertical-drilling technology. Vertical drilling is the principal technology employed during the period analyzed for this study, representing roughly 90% of all natural gas wells in the dataset. Horizontal drilling is more recent, and has only gradually gained mainstream appeal during the later part of the sample period. Additionally, it is easier to obtain precise production forecasts for wells drilled using vertical drilling technology, as horizontal wells are substantially more complex and technologically advanced (Ma et al., 2016). For example, Covert (2015) provides a clear illustration of the high level of detail necessary to properly characterize expected monthly production for horizontally drilled wells. Obtaining information at this level of detail is simply not possible when dealing with a relatively long-term dataset for the entire United States. At the same time, good production forecasts for vertical wells can be produced using information available from major data providers such as DrillingInfo. For all of these reasons, the study focuses exclusively on vertically drilled wells.

B. *The Life Cycle of Natural Gas Fields*

The commercial life cycle of natural gas has two stages: exploration and development. According to the *U.S. Energy Information Agency* (i.e., EIA), the exploration stage involves documenting the geological potential of the field in question, and determining its economic viability. Once a firm has sufficient information for confirming the economic potential of the field, it is classified as a proven

reserve⁵ and the development stage begins.

This study focuses on the development stage, during which firms still face a high level of idiosyncratic risk despite having established that the field in question is a proven reserve. They do not yet know (i) the exact delineation of the natural gas field, (ii) the structure of the rock formations within it, (iii) the production potential of each drilling location, or (iv) the technical expertise required to optimally extract the resource. For firms drilling wells, this lack of knowledge translates into tangible operational risks, such as the risk of drilling a dry hole⁶. For example, Figure 2 illustrates the development of the Panhandle field in Texas over the period between 1960 and 2010. Figure 2.1 represents the initial estimation of the field boundary, while Figure 2.2 represents the field’s finalized boundary 50 years later. There are substantial differences between the expected and realized boundaries. Large sections that were initially identified as promising appear to have had limited potential ultimately. This example provides a clear illustration of how idiosyncratic risk remains at the micro-level even after a field’s economic potential has been confirmed at the macro-level.

C. The Structure of Natural Gas Exploration and Production Firms

Oil and gas companies establish their strategies at the uppermost levels of the corporate hierarchy (Graham et al., 2015), but surveying, wells’ selection, and specific drilling decisions require advanced technical expertise and site-specific information (Kellogg, 2011; Covert, 2015; Decaire et al., 2019). For this reason, lower-level managers, geologists, and engineers tend to evaluate and select projects (Bohi, 1998), working within the confines of strategic guidelines from their superiors. Additionally, oil and gas firms tend to organize their operational units by regions. For example, energy companies’ shareholder communication documents (e.g., 10-K) provide examples of how those geographical formations affect operations’ structure (see Figure 3). Finally, by allocating their total budgets across multiple regional units, firms expose the key on-the-ground decision-makers (i.e., the junior managers) to the risks of only a relatively small number of specific projects. This creates a divide between idiosyncratic risk diversification measured at the firm level, and diversification

⁵The American Bar Association’s definition of proven reserves is as follows: The amount of oil and gas is estimated with reasonable certainty to be economically producible. source: American Bar Association, Oil and Gas Glossary, 2019.

⁶A dry hole is a well that fails to produce enough natural gas to be economically viable.

measured at the level of individual managers, potentially creating incongruities in risk preferences.

III. The Dataset

The present study uses a dataset provided by DrillingInfo⁷ covering all natural gas wells drilled in the United States between 1983 and 2010 (see Figure 4). Ultimately, the dataset contains 30,420,544 month-well observations used to estimate the well production function, a total of 114,969 distinct gas wells, and 369 distinct firms. The dataset includes monthly production for each project along with a set of projects' characteristics such as rock formation features, wells' GPS location, the royalty rate⁸ and the depth of the well. I augment these data points with two hand-collected datasets. The first covers per-project capital expenditures including per-foot drilling costs, obtained from public filing from regulatory pooling documents, and estimated operational costs, estimated from firms' 10-K. The second is drawn from the EIA and corresponds to the three-year natural gas price forecasts and two alternative sources of natural gas prices (the Bloomberg natural gas futures prices, and the EIA wellhead state's natural gas prices). The EIA is a federal reporting agency producing an annual economic analysis for the oil and gas industry⁹. For public firms, the dataset is further augmented using Compustat. Finally, the information needed to compute each firm's weighted cost of capital is drawn from the 10-year risk-free rate available on the Saint-Louis Federal Reserve website, the Kenneth French oil and gas industry return, the Robert Shiller price-earnings ratio, and credit rating information from Capital IQ.

Finally, I make several refinements to the dataset. I restrict the analysis to firms drilling at least 10 wells in a given year¹⁰; because discount rates are estimated from the lower boundary of the firms' portfolios, it is reasonable to focus on firms that are at least moderately active during

⁷DrillingInfo is a trusted data provider for multiple federal agencies reporting on environment and energy matters. Studies conducted by the U.S. Environmental Protection Agency (EPA) and the U.S. Energy Information Administration (EIA) *Inventory of U.S. Greenhouse Gas Emissions and Sinks, 1990-2016* by the EPA and *Petroleum Supply Monthly (PSM)* by the EIA use this dataset, for example.

⁸The royalty rates correspond to an expense computed as a percentage of the wells revenue that goes directly to the land owners leasing the land for a given well. The royalty rate estimates are based on royalty percentages obtained from DrillingInfo for the leases signed in the United States in a given year.

⁹More specifically, the U.S. Energy Information Administration (EIA) is a statistical and analytical agency housed within the U.S. Department of Energy. The EIA collects, analyzes, and disseminates independent and impartial energy information to promote sound policymaking, efficient markets, and public understanding of energy and its interaction with the economy and the environment. The EIA is the nation's premier source of energy information and, by law, its data, analyses, and forecasts are independent of approval by any other officer or employee of the U.S. government. Source: https://www.eia.gov/about/mission_overview.php

¹⁰The main result is robust to alternative cut-off value of 6 and 14, for example.

the year of analysis. For less-active firms, it is harder to distinguish between the firms' discount rate and the quality of their opportunity set when using the revealed-preference strategy. This adjustment drops only 5% of wells in the initial sample. Additionally, all township-year subgroups with fewer than three wells drilled are removed, because the measure of idiosyncratic risk employed here relies on the standard-deviation for each township-year set. Finally, any wells with missing information are dropped from the dataset, along with any wells for which the initial production date is prior to the drilling date, as those clearly contain data entry errors.

The firms in the sample are relatively large, with an average total value of active wells of \$229.2 million. On average, the total annual drilling budget is \$60.3 million. The average firm invests \$11.3 million per year for a given field, or \$19.4 million per year for a given state (see Table I). The average vertical gas well in the dataset costs \$465,653 and produces 570,049 thousand cubic feet of natural gas over its lifetime. Together, these numbers indicate that the average firm in the sample is large and experienced, and it operates in multiple geographical areas in a given year.

IV. Firms' Expectations

To estimate a firm's discount rate, I must first estimate each well's expected cash flows. Since cash flows equal well output times the price of natural gas, I need to estimate firm's expectations of each variable.

In general, computing the expected production quantities independently from expected prices leads to potential biases. In most situations, projects' production flow is endogenously correlated with prices, such that the expected cash flow can be expressed as:

$$E[p_z \cdot q_{j,z,m}] = E[p_z] \cdot E[q_{j,z,m}] + Cov(p_z; q_{j,z,m}), \quad (1)$$

where p_z is the price of natural gas at time z , and $q_{j,z,m}$ is the natural gas production of well j at time z and age m (in months). If $Cov(p_z; q_{j,z,m}) \neq 0$ it would indicate that expected production flow and natural gas prices are jointly determined. However, in the case of gas wells, once the decision to drill has been made, the well's monthly production is determined by geophysical factors and is therefore independent of the state of the economy. In the case of vertical oil wells, Anderson et al.

(2018) show that firms do not alter production rates or delay production due to oil price changes. Indeed, once a well starts producing, managers have little ability to influence the production level without risking damage to the well. What this means is that effectively, production flow depends on local geophysical parameters such as the local rock type, the density of the natural gas deposit, and so forth, rather than on economic variables affecting natural gas prices. For this reason, I assume that the production flow is not correlated with variables that affect gas prices. Further supporting this assumption, the correlation between realized natural gas prices and wells' realized production flow is just -0.0034 in my sample¹¹. Thus, estimating expected quantities and expected prices independently should not result in biased outcomes. The process through which I obtain these estimates is described below.

A. *Firms' Expected Production*

Monthly production of vertical gas wells can be approximated using a petroleum-engineering model such as the Arp model (Fetkovich, 1996; Li and Horne, 2003). The Arp model is the classical production-forecasting equation, and nowadays is taught in most energy engineering courses (e.g., the University of Pennsylvania course Engineering in Oil, Gas and Coal). According to the Arp model, the predicted monthly quantities produced by well j equal

$$q_{j,m} = A_j(1 + b\theta m)^{-\frac{1}{b}}, \quad (2)$$

where m corresponds to the number of months since the well has been drilled, A_j corresponds to the well's baseline production level, and b and θ are decline-rate elasticity parameters. To approximate the Arp model, I linearize this equation to obtain a regression (see Appendix B for the full derivation):

$$\ln(q_{j,m}) = \alpha_0 + \alpha_1 + A_j + \sum_{k=1}^K \beta_k m^k + \epsilon_{j,m}, \quad (3)$$

¹¹This statistic corresponds to the correlation of the realized natural gas prices (i.e., the wellhead spot price provided on the EIA website) with the realized within-well's production flow computed for the entire well-month sample.

where α_0 and α_1 are dummy variables for the first and second months of production, used to account for ramping production¹², K is the order of the linear approximation (i.e., 7), and $\epsilon_{j,m}$ is the regression’s error term.

The production baseline (i.e., A_j) represents the expected quantity of gas that will be initially produced by the well. I allow A_j to depend on the firm’s total experience (i.e., the total number of wells the firm has drilled before well j), the firm’s local experience (i.e., the number of wells the firm has drilled in the given township at the time of drilling j), the level of local information available (i.e., the total number of wells that have been drilled in the township at the time of drilling j), a firm-year fixed effect, and a township-year fixed effect such that:

$$A_j = \ln(\text{Firm's Local XP}_j) + \ln(\text{Firm's Total XP}_j) + \ln(\text{Local Info}_j) + \alpha_{i,t} + \alpha_{p,t} \quad (4)$$

Where i identifies the firms that drilled well j , p identifies the township in which the well is drilled, and t is the year the well is drilled.

Several recent papers motivate the addition of these controls for the Arp estimation (Covert, 2015; Decaire et al., 2019; Hodgson, 2019). Firms’ experience levels, peer effects, and local access to information influence the quality and type of projects a firm will undertake. More experienced firms are more likely to produce high-quality wells and to identify regions with better potential. Equally, regions with more activity are more likely to have wells of higher quality, while at the same time affording more precise information about how best to extract the resource. Because the goal of this part of the analysis is both to obtain precise estimates of the wells’ expected production flow and to deliver a reasonable measure of the wells’ idiosyncratic productivity shocks, it is important to control for factors that capture those characteristics.

Finally, to obtain the wells’ expected production flow, I proceed in two steps. First, I use the Arp model to estimate regression (3), using a sample of 30,420,544 month-well realized output (see Appendix Table I). Then, I use the Arp model estimates to obtain a measure of the managers’ expectation for each well in the sample. Figure 5¹³ provides a graphical illustration for the median

¹²A well’s ramping period usually corresponds to the first two months of production, during which firms’ engineers optimize and adjust the well’s production to reach peak long-term capacity (Dennis, 2017). Production then gradually declines until the well is dry.

¹³The ramping up period, encompassing the first two months of production, is excluded in order to capture production decline from peak production to termination.

well production function over time and contrasts it with the estimated production output. These expectations constitute the basis of the analysis to obtain a measure of the discount rate, and a measure of the wells' idiosyncratic risk.

B. Firms' Expected Price

I define the expected gas prices using the EIA's yearly three-year natural gas price forecast, at the time of drilling the well¹⁴. The EIA forecast is closely followed by governmental organizations, financial institutions, and energy companies. Section 9 explores alternative price specifications, such as the Bloomberg natural gas futures prices and wellhead spot prices varying at the level of individual states, and how these affect the results reported below. The EIA data are preferable to those other options for two reasons, however. First, the EIA three-year natural gas forecast has been published consistently since 1983, while the Bloomberg three-year natural gas futures contracts started trading only in 1995. Thus, the longer period for the EIA forecast allows the analysis to extend over a correspondingly greater duration. Second, although the wellhead state-by-state prices provide information on price variation across states during a given year, which helps to take into account cross-sectional variation of natural gas prices, those wellhead prices fail to account for managers' future expectations about price variation, making them unsuitable for the analysis. Finally, the EIA three-year forecast horizon is well matched to the present study, as the discounted half-life¹⁵ for projects in the sample is 31 months.

V. Estimating Firms' Discount Rates Using a Revealed Preference Strategy

A. Estimating Projects' Expected Rates of Return

To obtain estimates of firms' discount rates, I proceed in four steps. First, for each well a firm drills during a given year, I estimate the well's expected cash flows using forecasts of the well's production and natural gas prices. Second, I use those forecasts to compute the expected IRR (μ_j)

¹⁴A similar assumption for the prices is used in Kellogg (2014), Covert (2015) and Decaire et al. (2019).

¹⁵The discounted project half-life corresponds to the amount of time required for managers to obtain half of the discounted project's expected cash flow.

of each project j by solving the equation

$$\sum_{m=1}^M \frac{1}{(1 + \mu_j)^m} \mathbb{E}[q_{j,m}] \mathbb{E}[p_j] - C_j = 0, \quad (5)$$

where $\mathbb{E}[q_{j,m}]$ corresponds to the expected monthly production for well j at age m (in months)¹⁶, $\mathbb{E}[p_j]$ corresponds to the EIA 3-year natural gas price forecast at the time of drilling well j net of operating costs and royalty rate¹⁷, and C_j corresponds to the initial drilling cost incurred when the well is established. And as a final parameter, the average well in the sample produced for a total of 264 months (i.e., $M=264$).

B. Estimating Firm-Year Discount Rates

In the third step of the revealed preference strategy, for each firm in a given year, I split the wells into two portfolios based on their level of idiosyncratic risk. Projects with a measure of idiosyncratic risk above (below) the firm-year median are put in the high (low) idiosyncratic risk portfolio. Finally, the discount rates are estimated with the projects' lowest expected performance in each of the portfolios for each firm-year. The logic is that the firm's discount rate for that risk profile must be at least this low; otherwise these projects would not have been undertaken. Precisely, the estimated discount rate corresponds to the average expected IRR among the projects contained in the lowest 5th percentile of the portfolios' expected IRR distribution. In Section 9, I explore several alternative discount rate cut-off definitions, and the results are not economically or statistically affected.

Estimating discount rates based on two firm-year portfolios in this way provides multiple benefits. First, it simplifies the task of building a direct measure of the price of idiosyncratic risk for a given firm-year in order to directly test the effect of idiosyncratic risk pricing on firms' performance (see Section 7). Second, it makes it possible to include a regression specification that controls for

¹⁶I adjust the expected quantities from the Arp model for the probability of having no production during a given month. Adjusting for the probability of no production is necessary since the Arp regression uses the natural logarithmic value of the well production, thus excluding production event equal to 0. More specifically, $\mathbb{E}[q_{j,m}] = \mathbb{E}[q_{j,m} * (1 - Pr(\text{zero production in month } m))]$. I follow the methodology developed by Covert (2015) to adjust the production estimates for the zero production events. According to this method, I estimate a linear probability model to estimate the probability of having a no-production event, such that the probability of a month with zero production is 0.028 in the first year, 0.029 in the second year, 0.031 in the third year.

¹⁷ $\mathbb{E}[p_j] = \mathbb{E}[\text{Gas Price}_j] * (1 - \text{Royalty}_j - \text{Operational Cost})$

a firm-year fixed effect. However, to show that the results are not sensitive to this research design choice, I provide an alternative specification where I estimate the discount rate from one portfolio per firm-year in Section 9. The results are robust to this specification.

In this study, I only observe the set of projects each firm completes in a given year. In other words, I observe a truncated distribution of projects' expected IRR, because it is not possible to observe the expected return for projects the firms did not pursue (i.e., those that are not completed). At the same time, a firm may not have had investment opportunities with an expected IRR sufficiently close to the firm's discount rate. This means that my estimate constitutes an upper bound for the firms' discount rate. To mitigate concerns about this upper bound, I restrict the analysis to a subset of firms that drill at least 10 wells in a given year. The intuition is that for firms that drill many wells, the marginal well is more likely to represent the firms' lower bound (i.e., the firm's discount rate). Then, to validate that the estimates accurately capture the main features attributed to firms' discount rates, I conduct a robustness test. First, I restrict the analysis to the subset of firms whose full capital structure is observed. For that group, I compute the WACC. I obtain an estimate for the cost of equity in two steps. First, I use the one-year¹⁸ oil and gas industry capital asset pricing model (CAPM) beta computed at the monthly frequency, obtained from Kenneth French's industry return data¹⁹. Then, I multiply this variable by the expected equity premium, estimated from the earning-to-price ratio obtained from the Robert Shiller's website²⁰. Finally, to obtain the cost of debt, I collect the firms' yearly credit rating from Capital IQ (see Appendix A.2.). Table II presents the results of this test. There is a positive and statistically significant correlation between the discount rate estimates and the firms' WACC. Coefficient β_1 indicates that a one-percentage point increase to the firm WACC results in a 1.3 to 1.5pp increase in the discount rate²¹. The results presented in columns 3 and 4 of Table II suggest that the idiosyncratic risk premium is added to the discount rate on top of the WACC, and also that the

¹⁸Results are robust when using CAPM betas computed with other horizons, such as two-year and three-year horizons.

¹⁹The oil and gas industry return is available within the 49 industries' returns breakdown. I verify the robustness of the results using the various industry breakdowns available on the Kenneth French website, and I obtain similar results in all cases.

²⁰I estimate the expected equity premium from the fitted value of the regression $[\frac{E_t}{P_t} - r f_t] = \alpha + \beta[\frac{E_{t-1}}{P_{t-1}} - r f_{t-1}] + \epsilon_t$, estimated for the period 1983 to 2010. In an alternative specification, I use Fama and French (2002)'s estimate of the equity premium (4.32%) for the entire sample period, and the results are statistically robust and remain qualitatively similar, although the coefficients are slightly smaller.

²¹In all specifications, the value of 1 is included for the coefficient β_1 's confidence interval.

discount rate measure behaves in a manner consistent with variations in the cost of capital.

VI. Measure of Wells' Idiosyncratic Risk

To estimate projects' average idiosyncratic risk, I proceed in three steps. First, I define the well's idiosyncratic productivity shock, denoted ζ_j , as the well's first-year cash-flow forecast error attributable to quantity uncertainty scaled by the well's drilling cost:

$$\zeta_j = \frac{\sum_{m=1}^{m=12} \mathbb{E}[p_j] * q_{j,m} - \sum_{m=1}^{m=12} \mathbb{E}[p_j] * \mathbb{E}[q_{j,m}]}{Cost_j} \quad (6)$$

$$= \frac{\mathbb{E}[p_j]}{Cost_j} * \sum_{m=1}^{m=12} [q_{j,m} - \mathbb{E}[q_{j,m}]] \approx \frac{\mathbb{E}[p_j]}{Cost_j} * \sum_{m=1}^{m=12} \underbrace{\epsilon_{j,m}}_{(*)} \quad (7)$$

Where (*) roughly corresponds to the Arp model forecast error over the first year of production. These well-level productivity shocks possess a set of characteristics well suited to capture the idiosyncratic production shock. The source of the forecast error captures the source of variation to well's profitability attributable to the wells' annual production, holding expected prices constant. I obtain wells' expected production using the Arp model, which controls for the firm-year fixed effect and township-year fixed effect, indicating that the idiosyncratic shocks are orthogonal to the firm-year and township-year information sets. Also, Gilje and Taillard (2016) show that wells' drilling costs are homogeneous within a year, further supporting the idea that the Arp production forecast errors drive the variation in productivity shocks at the firm-year level. Then, it is reasonable to assume that well-diversified investors will perceive such a source of uncertainty as purely idiosyncratic. To support this claim, Appendix Table II presents the results of a regression of the market excess return on the wells' idiosyncratic productivity shocks. In all regression specifications, the coefficient associated with the idiosyncratic productivity shocks is not significant, which indicates that there exists no correlation between the well's idiosyncratic productivity shocks and the market excess returns. In a CAPM based framework, having the well's shocks uncorrelated with the market excess return²² provides evidence in favor of the idiosyncratic nature of the shocks. Considering that the CAPM is the most likely asset pricing model used by the average investor (Berk and van Binsbergen, 2016), using this framework for the analysis appears reasonable.

²²In the CAPM framework, the investor's stochastic discount rate is a function of the market excess return.

Second, I measure the idiosyncratic risk for each township-year by computing the cross-sectional dispersion of the local wells' idiosyncratic productivity shocks. The strategy is designed to only capture the quantity uncertainty contribution to the cash flow uncertainty. It is useful to note that I achieve this by only using expected prices in ζ_j calculation, ignoring the price shock from the calculation. This is to ensure that idiosyncratic risk is truly calculated from local idiosyncratic shocks. This provides a measure of idiosyncratic risk at the township-year level that can be attributed to each well that is drilled in the specific township in that given year (see Figure 6.1). Third, to obtain a measure for the firm-year-portfolio level, I take the average of the idiosyncratic risk for all the projects completed. Ultimately, the sample average of the projects' average idiosyncratic risk is equal to 10pp, and its standard-deviation is 18pp.

This measure of idiosyncratic risk has several appealing features. First, it corresponds to the level of productivity uncertainty managers face in the first year for 1\$ of invested capital. Second, firms tend to pay attention to the drilling outcomes in their wells' closed vicinity (Decaire et al., 2019), suggesting that the level of cross-sectional dispersion for the township-year likely reflects the level of well's idiosyncratic risk as assessed by local managers. Third, the analysis is conducted at a yearly frequency. Thus, working with first-year risk provides a measure of risk that is computed at the frequency of the study's analysis. And finally, the information contained in the productivity forecasting errors, ζ_j , is plausibly orthogonal to the characteristics of the managing firm. The Arp regression controls include a firm-year fixed effect and a township-year fixed effect as well as the firm's local experience, the firm's global experience, and the amount of local information available at the time of drilling. Thus, the information contained in a given well's productivity forecasting errors likely corresponds to information that is orthogonal to the firm-year and geographic characteristics already assessed by the model.

To verify the validity of the Arp regression specifications, it is first necessary to test whether there is any spatial correlation between the production forecast errors across wells. The goal of the test is to make sure that variation in forecasting errors is not driven by other important spatial-economic factors omitted from the Arp model. I assess spatial correlations using the Moran's I coefficient, which ranges in value from -1 to 1. A coefficient equal to zero indicates no spatial correlation, while positive coefficients imply clustering of forecasting errors. In the present context, a positive Moran's I would suggest that the Arp model has omitted spatial factors. However, the

estimate of Moran’s I is close to zero, at 0.01, suggesting that the Arp model properly captures relevant spatial factors. Finally, Figure 7 plots the distribution of the wells’ idiosyncratic productivity shocks. The idiosyncratic productivity shocks distribution is centered at zero (i.e., the median value is 0.0007), but it is slightly leptokurtic.

Next, in order to confirm that the above measure of idiosyncratic risk is positively related to a greater occurrence of poor drilling outcomes, I examine the number of dry holes per township-year. For township-year subgroups in the upper half of the idiosyncratic risk distribution, there are on average 0.39 dry holes drilled; for township-years in the lower half, this value is 0.04. This corresponds to a one order of magnitude difference between the comparison groups, strongly suggesting that township-years with greater idiosyncratic risk consistently experience higher rates of negative drilling outcomes. To control for additional factors, I also estimate a Poisson regression²³. Appendix Table III displays a positive and statistically significant relationship between projects’ idiosyncratic risk and the probability of drilling a dry hole across all specifications. Specifically, a one-standard-deviation increase in the idiosyncratic risk measure is associated with 1.4 additional dry holes drilled in the township-year. This result provides further empirical support for the relationship between the measure of idiosyncratic risk and adverse drilling outcomes.

VII. Results

A. *Do Managers Price Idiosyncratic Risk?*

To test whether managers price idiosyncratic risk, I first estimate an OLS regression of firms’ discount rates and projects’ idiosyncratic risk. The regression includes two observations per firm-year, one for each of the firm’s high- and low-idiosyncratic risk portfolios. To simplify the interpretation of the regression coefficient across all the regression specifications in the paper, I scale the regressor of interest by its regression-sample standard-deviation²⁴. Table III shows that managers appear to positively price idiosyncratic risk. Column 1 presents the simple regression with one control, the portfolios’ potential differential exposure to systematic risk (See Appendix C for a complete

²³A Poisson regression is the appropriate model when the dependent variable is a count variable, such as the number of dry holes in a township-year (Greene, 2003).

²⁴To scale a regressor by a constant does not alter the statistical properties of the estimate (Greene, 2003). This strategy has the added benefit of directly providing me with the magnitude for the effect of a one-standard-deviation increase in the projects’ idiosyncratic risk.

discussion). Columns 2 to 5 introduce a set of controls and show that the regression results are robust to those further specifications. Column 6 includes a firm-year fixed effect, to control for the time-varying characteristics of firms, and Column 7 adds the idiosyncratic risk portfolio fixed effect. The source of variation in those regression is the relationship between average projects' idiosyncratic risk and the discount rates estimated for high- and low-risk firm-year portfolios. For the average firm, a one-standard-deviation increase in idiosyncratic risk results in a 6.7 to 8.0pp increase in the discount rate.

B. Instrumental Variable

The fixed effects included in the above regressions address a few endogeneity concerns. Specifically, the firm-year fixed effect accounts for the fact that, in a given year, a firm may systematically select regions that are riskier. At the same time, the idiosyncratic risk portfolio fixed effect helps address the idea that there might be a selection effect such that some unobserved variables (e.g., managers experience) might systematically be associated to better or riskier regions (i.e., regions with better potential projects, lower risk of bad drilling outcomes). However, the fixed effect strategy does not account for the managers' heterogeneity within the idiosyncratic risk portfolios, which could plausibly vary by firms. Thus, the previous OLS regression may suffer from a within-firm omitted-variable bias.

To address these additional endogeneity concerns, I take an instrumental-variable approach. The strategy is implemented in two steps. First, each well is associated with its corresponding township-year peers' largest project's idiosyncratic productivity shock. Figure 6 provides a graphical example with three firms (identified in **Red**, **Blue**, and **Black**) of how these shocks are identified for one particular township-year; for the wells drilled by the Red firm, the associated peer's shock is 0.23. Then, I define the instrumental variable as the average value of those associated peers' shocks computed at the level of each firm-year portfolio.

The relevance of the instrumental variable has to do with how the idiosyncratic risk variable is calculated. In this study, the idiosyncratic risk corresponds to the cross-sectional dispersion of all

the project-specific productivity shocks occurring within a township-year such that:

$$\text{Idiosyncratic Risk}_{p,t} = f(\zeta_j^{Red}, \zeta_j^{Blue}, \zeta_j^{Black}) \quad (8)$$

From the example in Figure 6, the projects' idiosyncratic risk measure for the wells drilled in that particular township-year, 0.129, corresponds to the standard-deviation of the 10 idiosyncratic productivity shocks. From the standpoint of the Red firm, the largest idiosyncratic productivity shock experienced by its Blue and Black peers in the township-year is 0.23. Then, given how the idiosyncratic risk variable is constructed, it is reasonable to assume that, on average, those peers' shocks will be correlated with the idiosyncratic risk variable. Panel A of Table IV reports the first stage of the instrumented regression, which provides empirical support for this assumption. The values of β_1 indicate that there is a positive relationship between idiosyncratic risk levels and the size of the largest idiosyncratic productivity shock that affects a firm's peers within a given township-year. Additionally, to address potential concerns about weak instruments, the bottom section of Panel A reports the Kleibergen-Paap first-stage F-statistic. For each regression specification, the statistic's value is substantially greater than the minimum threshold, ~ 10 , alleviating concerns regarding the presence of a weak instrument.

To satisfy the exclusion restriction, I use the peers' idiosyncratic productivity shocks within each township. From the Arp regression, I obtain the peers' idiosyncratic shocks after controlling for firm-year factors, township-year factors, as well as the firms' experience and information set. Then, if managers' assignment to specific regions is affected by these characteristics, the Arp model should make the information content of peers' shocks uncorrelated with those variables (see Section 7 for the full discussion of the idiosyncratic shocks). Then, after applying the fixed effect strategy in the instrumented regression, the peers' managers' characteristics should be uncorrelated with the firm's managers' characteristics within a portfolio's risk profile. As a sanity check, I verify if this assumption is supported empirically for the whole sample. In the context of Figure 6, this corresponds to testing if the idiosyncratic productivity shocks of the *Red* firm (0.05, -0.1) are correlated with the largest peer's idiosyncratic productivity shock, 0.23. More specifically, I regress each well's own idiosyncratic shock on their associated largest peers' idiosyncratic productivity shock, for the entire sample (i.e., the 114,969 distinct wells). While there exists no way to technically

test for the exclusion restriction, the absence of correlation is generally reassuring. Table V reports the regression results of the firm’s own idiosyncratic productivity shocks on the largest peers’ idiosyncratic productivity shock in each township-year. I find no statistical relationship between the two types of shocks, across all the regression specifications. Perhaps the most relevant specification is the one presented in column 8, because it addresses more directly the underlying assumption of the instrumental variable strategy: the absence of correlation between firms’ managers’ characteristics and its peers’ characteristics within a township of a given risk level. Specifically, column 8 suggests that there exists no statistical relationship between the shocks within a given township, providing support for the instrument assumption.

Panel B of Table IV reports the results of the second stage of the instrumented regression. The coefficients are slightly smaller in magnitude than the results obtained from the reduced-form regression, but they remain economically meaningful. For the instrumented regression, a one-standard-deviation increase in a project’s idiosyncratic risk results in an increase of 3.8 to 6.0pp in the firms discount rate, compared to 6.7 to 8.0pp for the reduced-form regression.

Regarding the sign of the endogeneity bias, I find that the coefficient of interest (β_1) of the instrumented regression is smaller than the one in the reduced-form regression presented in Table III, across all specifications (see Appendix D). The direction of the bias for the coefficient of interest (β_1^*) depends on (i) the covariance between the managers’ experience and the level of idiosyncratic risk associated with the wells, and (ii) β_2 , the linear relationship between managers’ experience and the firms’ discount rate. Ultimately, multiple within-firm omitted variables could be affecting my analysis, with some having opposing effects on the direction of the endogeneity bias. In this sense, the goal of the following discussion is to provide a concrete example to illustrate the type of omitted variables that appear to ultimately dominate the direction of the endogeneity bias observed in the reduced-form regression.

For (i), it is plausible that more experienced managers get assigned to better regions (i.e., better prospect, lower production risk) because of their greater bargaining power within the firm or that, given their higher level of experience, the outcome of their wells is less uncertain because they know better how to optimally extract the natural gas. In this specific framework, this would suggest a negative relationship between the managers’ level of experience and the observed idiosyncratic risk variable. For (ii), to obtain a reasonable explanation on the sign of β_2 , it is helpful to look at it from

a career concern standpoint. More experienced managers have a longer list of realizations, which suggests that each additional signal is less likely to have a large effect on how the firms' superiors update their belief of the experienced managers' worth. In this case, bad drilling outcomes are less likely to negatively affect how superiors value experienced managers than how they value unexperienced managers. Chevalier and Ellison (1999) provide empirical evidence in favor of this career concern explanation, showing that on average, less experienced managers are more likely to get fired for bad performance. This suggests that for a similar level of exposure to idiosyncratic risk, more experienced managers would require a smaller idiosyncratic risk premium than their less experienced counterparts, implying that the sign of β_2 should be negative. Ultimately, the combined effect of these variables would suggest that the reduced-form regression suffers from an upward bias because of omitted variables such as managers' experience. In other words, the coefficient obtained in the reduced-form regression may overestimate the magnitude of the discount rate adjustment to account for idiosyncratic risk, when compared to the true coefficient.

C. Idiosyncratic Risk Premiums and Firm Performance

The previous results have implications for firms' performance. If managers inflate their discount rate when faced with a high level of idiosyncratic risk, firms would then underinvest in wells with a high level of idiosyncratic risk. As a consequence, pricing idiosyncratic risk could have negative consequences for firms' performance, while abstaining from doing so should be correlated with relatively better performance. However, there is little empirical evidence linking firms' discount rate adjustment to adverse performance.

I directly examine that relationship here. To test for the effect of idiosyncratic risk pricing on firms' performance (e.g., gross profit margins, gross profitability, asset growth (YoY), and investment rate), it is necessary to develop a measure of firms' pricing of idiosyncratic risk, to directly use it as a regressor. To construct this variable, I define the numerator as the difference between the discount rates of the high idiosyncratic risk portfolio and the low idiosyncratic risk portfolio, and I define the denominator as the difference between the idiosyncratic risk measures of the two

portfolios²⁵, such that:

$$\text{Price of Idiosyncratic Risk}_{i,t} = \frac{\text{Discount Rate}_{i,t,High} - \text{Discount Rate}_{i,t,Low}}{\text{Idiosyncratic Risk}_{i,t,High} - \text{Idiosyncratic Risk}_{i,t,Low}}$$

where High and Low corresponds to the two firm-year portfolios sorted on the exposure to idiosyncratic risk. Effectively, this measure gives the discount rate change that corresponds to a one-unit increase in average projects' idiosyncratic risk, for each firm at a yearly frequency.

Table VI relates firms' price of idiosyncratic risk to their performance. For the average firm, a one-standard-deviation increase in the price of idiosyncratic risk has a statistically significant and sizable negative effect on the gross profit margins (-5.1pp), investment rate (-0.8pp), year-over-year asset growth (-0.7pp), and gross profitability (-0.5pp). The negative relationship between firms' performance and the firms' pricing of idiosyncratic risk suggests that idiosyncratic risk pricing is related to one or more forms of resource misallocation.

D. Mechanisms

This section explore several potential mechanisms that might induce managers to adjust discount rates to account for idiosyncratic risk. The mechanisms relate to theories that focus on either external pressures (frictions between the firm and the financial market) or internal pressures (frictions between managers and their superiors).

D.1. The Cost of External Funding and Idiosyncratic Risk Pricing

Firms dispose of multiple tools to manage their exposure to risk. While most of the discussion in the literature has focused on the use of financial derivatives, other mechanisms have long been acknowledged. Studying the interaction between risk management and capital budgeting, Froot et al. (1993) make the empirical prediction that managers would adjust their discount rate to account for risk that cannot be offloaded in the financial market in the presence of costly external financing. Risks that cannot be hedged expose the firm to variability in cash flows. In the context of this paper, this can be understood as drilling wells that would not produce enough natural gas (e.g., a dry hole). If the projects that a firm pursues fail to produce cash flow, the firm may then

²⁵The calculation details are available in Appendix A.1.

have to turn to external markets to raise additional funds and continue its operations. However, if the cost of marginal funds increases with the amount raised, the firm might have to limit its investment in the next period or raise capital from increasingly expensive sources. In this sense, greater variability in the wells' outcome exposes firms to a greater probability of having to raise external funds at a premium. Since this source of risk directly translates into a greater cost of capital, Froot et al. (1993) suggest that managers should adjust their discount rate calculations accordingly.

Obtaining a measure of the cost of external financing is challenging, as researchers do not directly observe this variable. To test the hypothesis, this study builds on the work done by Hennessy and Whited (2007), which provides empirically-based guidance for selecting the best proxy of costly external financing. The core of their analysis focuses on firms' size as well as three indexes: (i) the Cleary index, (ii) the Whited-Wu index, and (iii) the Kaplan-Zingales index. In general, they conclude that firm size is the best proxy for the costs of external financing, where larger firms face a lower costs of external financing than do their smaller counterparts. They also, however, find that the Cleary index and Whited-Wu index properly capture most of the dynamics attributed to the cost of external financing, but fail to behave adequately with respect to the costs of bankruptcy, making them inaccurate overall proxies for the cost of external financing. Finally, the authors note that the Kaplan-Zingales index improperly captures most of the dynamics attributed to the cost of external financing. On this basis, the authors conclude that firm size is the best proxy for costly external financing, noting that the three indexes are better suited to act as proxies for the need for external funding rather than for its cost.

All four of these potential proxies are included here, in an effort to be fully transparent. In addition, the present study includes firms' status (i.e., public or private) and the Hadlock-Pierce index as additional proxies. Private ownership status has been associated with higher financing frictions in the finance literature (Gao et al., 2013) and thus has the potential to be informative here. Also, there is empirical evidence suggesting that the Hadlock-Pierce index captures firms' financial constraints. Although the index has not been tested in the Hennessy and Whited (2007)'s costly external financing horse race analysis, it is closely related to the firm's size proxy discussed by Hennessy and Whited (2007) as it is a function of firm size and age.

Table VII and Appendix Tables IV to VIII present the results of each of the six proxies of costly

external financing. For each table, the coefficient β_2 measures the effect of costly external financing on firms' pricing of idiosyncratic risk. Columns 5 through 8 of each table present the results when two variables are instrumented: (i) the projects' idiosyncratic risk variable and (ii) the interaction of projects' idiosyncratic risk with the relevant proxy of costly external financing (i.e., β_1 and β_2).

Table VII reports the results of firm size. Consistent with the analysis of Froot et al. (1993), it shows that as the cost of external funding decreases, firms tend to price idiosyncratic risk less aggressively. The results are robust across all specifications, for both reduced form and the instrumented regression. On average, a one-standard-deviation reduction in firm size results in a 2.3pp increase in the price of idiosyncratic risk²⁶. Columns 2, 3, 4, 6, 7, and 8 introduce a proxy for firms' diversification²⁷, which corresponds to the firm-level idiosyncratic risk diversification among all the projects that are drilled for a given firm-year. The diversification variable is included because firms' size has been associated with several other characteristics of firms, such as their ability to diversify sources of idiosyncratic risk (Demsetz and Strahan, 1997). The firms' annual budget diversification variable is constructed in a similar spirit to the diversification index in Seru (2014) (see Appendix A.1.), and a larger value of the variable indicates that a larger share of the idiosyncratic risk is diversified at the firm level.

Appendix Table IV reports the results for the Hadlock-Pierce index, which are directionally consistent with the section hypothesis, and statistically significant. Namely, when the Hadlock-Pierce index increases, which indicates that firms are more financially constrained, firms' price idiosyncratic risk more aggressively. Appendix Table V presents mixed results for the effect of firms' ownership status. For the specifications excluding a fixed effect at the firm level, the results are consistent with the prediction made by Froot et al. (1993), such that private firms' price idiosyncratic risk more than public firms, but the difference is not statistically significant. Appendix Tables VI to VIII report the Cleary, Whited-Wu and Kaplan-Zingales indexes results. They are directionally consistent with the theoretical prediction developed in Froot et al. (1993), but they are not all statistically different from zero.

Overall, the results presented in this section suggest that the cost of external financing can have a meaningful impact on how firms adjust their discount rates. Focusing on Hennessy and Whited

²⁶From Table VII: $\beta_2 * \text{Average Scaled Idiosyncratic Risk} * \sigma_{\text{Asset}} = -0.01 * 0.6 * 383.8 = -2.3$.

²⁷Appendix A.3. provides the details of the calculations involved.

(2007)'s favored measure, the results indicate that costly external financing can induce managers to price the undiversified quantities of idiosyncratic risk. It is reasonable to assume that this proxy imperfectly captures attributes associated with firms' cost of external financing, and thus it could ultimately suffer from endogeneity bias. However, most of the additional proxies tested in this section provide results that are directionally consistent with that theoretical prediction (despite not being all statistically significant), lending further strength to that finding.

D.2. Managers' Budget Size Diversification and Idiosyncratic Risk Pricing

Survey evidence collected by Graham et al. (2015) suggests that specific investment decisions are formulated at the lower level of the hierarchical structure, while budget allocation is decided by the firms' superiors. Geanakoplos and Milgrom (1991) suggest that delegating investment decision-making to the agents with the highest amount of information regarding a specific decision improves resource allocation. Empirically, the delegation of authority has been linked to team specialization (e.g., Caroli and Reenen (2001); Colombo and Delmastro (2004); Acemoglu et al. (2007)), where workers in jobs that require technical skills usually benefit from a greater level of authority. In the context of gas exploration and production companies, this approach increases the likelihood that people most familiar with the local rock formation specificity will make investment decisions with limited interference (Bohi, 1998). However, the decoupling between the capital allocation choice and the decision to invest in specific projects, known as the delegation process, has been argued as a potential source of agency conflict between managers and their superiors (Aghion and Tirole, 1997). From the lens of Aghion and Tirole (1997), to delegate land surveying and project selection can be beneficial for firms since specialized on-site managers are more likely to generate quality information and then identify better drilling opportunities. However, by giving managers a high level of autonomy, there is a risk that managers might try to abuse their authority and misrepresent the full set of available wells when pitching them to the firms' superiors, if monitoring is costly. For example, managers might prefer to avoid pitching projects with an associated idiosyncratic risk measure that exceeds their preferred level, although those wells could be value creating from the firms' standpoint. This could be the case if managers are evaluated, and ultimately *rewarded* or *punished*, by demonstrating their ability to generate production forecasts that are, on average, in line with the wells' realized production. For the firms, managers' ability to produce reliable

production forecasts on average can be appealing since it facilitates the efficient allocation of resources. Firms' superiors might value this type of ability in managers' performance reviews. Thus, for managers, choosing wells with a higher level of idiosyncratic risk increases the probability of being wrong in the production forecast (above or below) of a given well, which could increase their risk of receiving bad evaluations. Although my dataset does not enable me to observe managers' compensation contracts or if they get fired or promoted based on their forecasting performance, Table VIII provides empirical evidence suggesting that firms' resource allocation responds to forecasting *mistakes*. Precisely, the regression results reported in Table VIII indicate that firms allocate a smaller share of the annual budget in the following period to managers for which the realized production diverges more from the expected production in the current period. This result is robust when controlling for a region-year fixed effect, a factor that captures regions' overall production potential and quality.

A direct consequence of the delegation process is that firms' high-level decision-makers allocate the firm's total budget across multiple managers, each tasked with evaluating, selecting, and pitching projects to the firms' superiors that should, in principle, maximize the firm's value. The fact that managers receive a fraction of the firm's budget can result in a loss of diversification at the manager level, in the sense used by Diamond (1984). The general response from the finance and economic literature to this type of agency friction is to design a compensation contract that would mitigate the friction. However, given the complex nature of real life situation, it appears reasonable to think that such wage contract might not be feasible in practice. In this sense, Holmstrom and Costa (1986) suggest that capital budgeting policies can play a partial role. For a risk-averse manager, if projects' idiosyncratic productivity shocks are not perfectly correlated among themselves, being granted a larger budget has two effects. First, it reduces the total quantity of idiosyncratic risk they face. And second, it decreases the manager's idiosyncratic risk premium. The insight developed in Diamond (1984) would suggest that firms in which managers have larger budgets should, all things being equal, price idiosyncratic risk less aggressively.

That hypothesis is directly tested here. First, I construct a measure to proxy for managers' idiosyncratic risk diversification: managers' budget size. Natural gas exploration and production companies organize their activities into regional units. Although it is difficult to delineate the exact region covered by each manager, it is still possible to develop multiple proxies of managers' budgets

based on a plausible definition of region of activity. The procedure followed here considers two potential scenarios that represent a lower and an upper boundary for the size of their assigned territory, such that managers could either be assigned to a specific field or to a specific state. Assuming that managers are assigned to specific gas fields is a reasonable lower boundary, as each field possesses unique characteristics for which the required technical expertise cannot be directly mapped onto other locations (Kellogg, 2011). These particularities create a steep learning curve for managers taking on new fields and limit managers' ability to transfer their knowledge. At the other extreme, using states as managers' assigned territories presents a plausible upper boundary. Indeed, it matches job postings' regions of assignment and how organizations determine the territory of their regional units. For each of these two scenarios, I then estimate the managers' budget size in two steps. First, I calculate the total cost for all wells drilled in a given field or state for each firm and year. Then, I define average managers' budget as the average value across all fields/states at the firm and year level. This provides me with the average budget size of the firms' managers in that given year, for each of two possible methods of measuring the budget allocation.

Table IX presents the results of the regression assuming that individual fields define managers' region of activity. Coefficient β_2 measures the effect of managers' budget size on firms' pricing of idiosyncratic risk. In line with Diamond's proposal, managerial budget size appears to have a meaningful impact on idiosyncratic risk pricing. A one-standard-deviation increase in average budget size results in a reduction of 1.16pp²⁸ in the price of idiosyncratic risk. Appendix Table IX presents the results of the same tests when managers are assumed to operate at the level of an entire state. The results are robust to this alternative specification for the region of activity; the relationship is similar in both cases. Finally, Appendix Table X shows a positive and statistically significant relationship between managerial budget size and projects' levels of idiosyncratic risk. This is further evidence suggesting that managers' risk tolerance increases as a result of increasing budget size.

To further support the agency channel effect, I test how the effect of managers' budget size varies as a function of agency friction. To do so, I construct a measure of agency friction building on the insight that proximity facilitates monitoring and information acquisition by the firm's superiors. A rich empirical literature presents evidence illustrating the benefits of proximity in reducing the

²⁸From Table IX: $\beta_2 * \text{Average Scaled Idiosyncratic Risk} * \sigma_{\text{Managers' Budget}} = -0.11 * 0.6 * 17.6 = -1.16$.

cost of acquiring information and improving monitoring. Giroud (2013) presents evidence suggesting that proximity between firms' headquarters and plants reduces agency conflict by improving the ability of superiors to go on-site and directly monitor plants' managers. Similarly, Coval and Moskowitz (1999) and Coval and Moskowitz (2001) show results with mutual fund managers, where proximity enables funds' managers to obtain better results with the shares of firms located geographically closer, suggesting better monitoring capabilities and access to private information. I obtain the measure of proximity by calculating the median distance between the wells drilled by a firm in a given year²⁹. In the context of this literature, a greater median distance between the firms' wells indicates greater difficulty in monitoring the quality of projects for the firms' superiors, thus corresponding to a greater level of agency problem. Given this, if budget size affects managers' risk tolerance through the agency channel, one would expect that the effect of budget size be more salient in firms experiencing greater agency conflict. Table X reports the results of this additional test. The variable of interest is associated with the coefficient β_3 . The negative coefficient suggests that as firms face more agency problems (i.e., a greater distance between the wells), the effect of budget size in mitigating the agency friction becomes stronger.

The results reported in this section suggest that managers' budget size has a meaningful effect on managers' risk tolerance, ultimately reducing managers' pricing of idiosyncratic risk. It suggests that, for the average firm, the set of available tools to alter managers risk tolerance extends beyond compensation contracts. By shifting the allocation of resources among its managers, firms can provide a form of insurance for those who are, for instance, overly risk-averse.

D.3. Costly External Financing and Agency Frictions

To further explore how the two mechanisms affect the price of idiosyncratic risk, I investigate their combined effect. Table XI reports the results of the regression that includes proxies for both mechanisms as well as their interaction term. Across all specifications and for both proxies of managers' budget size (i.e., aggregation at the field or state level), I find that the price of idiosyncratic risk (β_1) is positive and statistically significant, such that a one-standard-deviation increase is associated with a 10.5 to 12.7pp increase in the discount rate. In addition, including

²⁹In a first step, I measure the distance between all the wells a firm drilled in a given year. Then, the agency friction value is defined as the median value of those distances, for each firm-year.

both mechanisms simultaneously does not eliminate their individual contribution. Particularly, both mechanisms (β_2 and β_6) are statistically and economically significant, and their magnitudes are close to the ones obtained in Tables VII, IX and Appendix Table IX. These results provide additional evidence suggesting that both mechanisms operate jointly on frictions associated with the firms' price of idiosyncratic risk. Perhaps more interesting is the coefficient β_7 , which represents the contribution of the interaction between the two mechanisms to the price of idiosyncratic risk. The coefficient is positive and statistically significant, although its magnitude is almost zero³⁰. To interpret this coefficient, it is useful to look at a simple case. For a fixed level of idiosyncratic risk, we can look at two firms with different sizes: 0 or 1. In this example, managers' budget size will be less effective in reducing the price of idiosyncratic risk ($\beta_6 + \beta_7$) for larger firms (i.e., firms of size 1). I interpret this result such that, when holding the level of idiosyncratic risk constant, the marginal benefit for increasing the size of managers' budget is smaller for firms that are less exposed to costly external financing frictions. A similar reasoning can be applied to firms' size.

VIII. Robustness Analysis

In this section, I conduct several robustness tests to rule out alternative explanations.

A. *The Effect of Real Options*

One potential concern with the strategy adopted here for estimating firms' discount rates is whether it adequately accounts for important aspects of firms' project selection. For example, managers might use a real option investment threshold, rather than project cost, to calculate projects' NPV; the real option literature (Dixit and Pindyck, 1996) explicitly considers idiosyncratic risk when determining optimal exercise thresholds. If this is the case, failing to account for the firm projects' *optionality feature* could substantially alter the nature of the above results.

Empirical evidence suggests that managers behave in a way that is directionally consistent with real option theory (Bloom et al., 2007; Kellogg, 2014; Decaire et al., 2019), although they also systematically exercise their investment opportunities prior to the real option recommendation. Brennan and Schwartz (1985) (in the case of gold mines), Kellogg (2014)³¹ (on oil wells), and

³⁰I divided the variable by 1000 to increase the coefficient magnitude and show digits in the regression table.

³¹See Figure 10 of Kellogg (2014).

Decaire et al. (2019) (on shale gas wells) provide empirical evidence in support of this claim. This suggests that managers do not follow the recommendation of real option theory strictly—a situation that is further supported by multiple survey-based studies (Graham and Harvey, 2001; Jacobs and Shivdasani, 2012; Graham et al., 2015). Instead, in more than 90% of cases, managers prefer more straightforward and less capricious valuation strategies such as NPV and IRR when selecting projects (Graham and Harvey, 2001), with little mention of the use of real options. In this light, it is reasonable to assume that managers acknowledge to some extent the value and importance of operational flexibility, but real option models might be too stylized to properly capture the *exact* dynamic. Nonetheless, I use two methods here to ensure that the present results are robust to the effect of operational flexibility and real option.

First, to directly alleviate the concern that this study is biased by a *operational flexibility* factor, I repeat the above analysis using a restricted sample of projects that are minimally likely to be affected. Precisely, I focus on wells for which managers have little time to drill, since real option valuation directly depends on the flexibility of a project’s timing. Speaking generally, the more time the managers have to decide when to invest in their projects, the more the real option is worth. Now, there are two ways a firm can obtain the right to develop a plot of land in the United States. It can either acquire a lease, providing the exclusive right to the plot during a certain period, which is, on average, three years, or it can “hold [the development rights] by production”. This means that as long as a firm has an actively producing well on the plot, they are entitled to further develop it until they fully deplete the available reserves of natural gas. In these cases, firms usually have 20 years or more to drill additional wells. Papers investigating real option behavior have traditionally focused on projects whose lands are controlled through this second mechanism, because the real option phenomenon is more salient in those cases (Decaire et al., 2019). However, when operating on a leased plot of land, oil and gas exploration companies tend to drill their first well immediately prior to the expiration of the lease (Herrnstadt et al., 2019). Thus, for those first wells, the effective value of the option-to-wait at the time of drilling is marginal. Effectively, as the real option time to expiration converges toward zero, its value also converges to zero. Given this, the first strategy used here is to limit the analysis to only those wells that are the first to be drilled on a given plot of land. For those wells, managers faced limited operational flexibility.

The second strategy is to adjust the revealed preference strategy described above to directly

account for the *real option* value. This is done by modifying the decision rule used when estimating each project’s expected IRR. Rather than assuming that firms choose to invest whenever a project’s expected cash flow is greater than its cost, the new rule assumes that firms use a real option optimal exercise threshold that increases along with a project’s level of idiosyncratic risk such that the decision rule becomes (see Appendix E for a detailed explanation of the real option calculation):

$$\sum_{m=1}^M \frac{1}{(1 + \mu_j)^m} \mathbb{E}[q_{j,m}] \mathbb{E}[P_j] - V_j^* = 0 \quad (9)$$

Where V^* is the real option optimal exercise threshold as specified by Dixit and Pindyck, such that $V_j^* = \frac{\beta_j^1}{\beta_j^1 - 1} C_j \geq C_j$.

There are two limitations to this strategy, however. The first is related to the amount of time to expiration for each project. Because this information is not observed for most wells in the dataset, the most conservative approach is to assume that firms have an infinite time horizon to exercise their options for all projects. The real option optimal threshold is increasingly sensitive to projects’ risk as the time to expiration increases, thus giving each project an effectively infinite duration before expiration corresponds to a more conservative scenario here (Dixit and Pindyck, 1996). The second limiting factor is related to the measure of idiosyncratic risk. There could be concerns that the measured level of the idiosyncratic risk is too low, and that it does not properly capture the total quantity of idiosyncratic productivity risk faced by the firms. In turn, this would bias the real option test. To test the robustness of the results with the calibrated real option, I design a kill test. Precisely, when calibrating the real option optimal threshold, I increase the measure of idiosyncratic productivity risk to find at which level my core result is no longer statistically significant. Multiplying the magnitude of idiosyncratic productivity risk magnifies the difference between the riskier wells and the less risky ones, ultimately widening the difference between the real option exercise threshold, which reduces the difference between the estimated expected IRRs.

Table XII presents the results of the first strategy and Appendix Table XI present the results of the robustness test for the real option effect. Both regressions are qualitatively and statistically similar to the primary results described in earlier sections, suggesting that a operational flexibility or real option effect is not significantly altering the reported outcomes. Not surprisingly, the regression coefficients are lower in all specifications, suggesting that some of the observed variation

might be partially attributable to those phenomenon. Also, the number of observations in both tables is lower than that in the main regression tables. For Table XII, it is because most of the projects evaluated in this analysis are infill wells (i.e., wells drilled when the plot of land is *held by production*), which reduces the number of firms included in the sample. Similarly, for Appendix Table XI, the number of observations for the real option calibration specification is lower than the one for the main specification, because implied volatility data is not available on Bloomberg before the year 2000. Finally, the results of the kill test indicate that the core results of this paper are robust to the real option calibration up to an increase of 28.8% of the idiosyncratic risk.

B. The Effect of Firms' Leverage

The cost of debt for a given firm increases with the total amount of risk incurred at the firm level (Merton, 1974), including both systematic and idiosyncratic forms of risk. Taksler (2003) presents empirical evidence in favor of Merton's theory, which is roughly that a firm's weighted cost of capital should account for the firm's idiosyncratic risk, through its debt component. To test for this alternative interpretation, I design a separate regression that includes firms' market leverage and an interaction term of market leverage with project-level idiosyncratic risk, including only those firms for which the relevant information is available. Table XIII reports the results of that test, which are that the effects of leverage on the price of projects' idiosyncratic risk does not economically or statistically alter the above results. Also, consistent with the effect of leverage discussed in Merton (1974), the coefficient of the interaction between firms' leverage and the projects' average idiosyncratic risk (i.e., β_5) is positive, but not statistically significant in all regression specifications. The directional effect is consistent with the phenomenon discussed by Merton, such that idiosyncratic risk should be priced by the debt component of firms' capital structure.

C. Asset Pricing and the Idiosyncratic Risk Premium

A well-established asset pricing literature has found that firms' returns may account for idiosyncratic risk. For example, Goyal and Santa-Clara (2003) found a positive relationship between the quantity of idiosyncratic risk measured at the firm level and the returns on the market, while Ang et al. (2009) finds that firms with high past idiosyncratic volatility have low future average

returns. This literature has discussed the role of investors lack of diversification and the role of real options to explain the idiosyncratic risk premium. There is a possibility that the results observed in my study are affected by this dynamic. However, three pieces of evidence presented in the previous sections provide reassuring evidence regarding such concerns. First, Table II coefficient β_2 indicates that firms price idiosyncratic risk after controlling for the WACC or the cost of equity, which proxies for the *idiosyncratic risk premium* discussed in the asset pricing literature. Second, Appendix Table V shows that the results are robust to firms' listing status (i.e., private or public), ruling out the idea that the observed phenomenon is driven by a stock market effect, since it is observed for both types of firms. Finally, the mechanisms explored in this paper indicate that a plausible explanation for the observed dynamic is attributable to firms internal frictions, steering away from a solely financial market effect.

D. Alternative Price Specifications

The study's primary results are also robust to two alternative price specifications. The first alternative uses the three-year Bloomberg natural gas futures contract prices rather than EIA three-year forecast³². In the second specification, the EIA regional wellhead prices are used to account for price heterogeneity across states (see Figure 8). Effectively, the price firms obtain for selling their product can vary across regions, depending on the *quality* of the resource and the distance it must be transported in order to reach a refinery site. Tables XIV and XV report the results of these two additional specifications. In both cases, the primary results are not qualitatively or quantitatively altered.

E. Alternative Research Design

To address the concern that the above analysis might be affected by the specific nature of the research design selected here, I test an alternative design. Instead of constructing two portfolios for each firm-year subsample according to the idiosyncratic risk exposure of each project, this alternative design includes only one portfolio per firm-year subsample, inclusive of all projects. Table XVI displays the regression results obtained when estimating firms' discount rates using this

³²The number of observations is smaller than the main specification used above, because Bloomberg's three-year natural gas futures prices are only available from 1995 to 2010, which presents a restricted sampling window.

approach. The coefficient estimates are not meaningfully affected by the alternative experimental design; the only practical difference is that the regression cannot be modified to include a firm-year fixed effect, as there is only one observation per firm-year.

F. Alternative Discount Rate Thresholds

I introduce two alternative threshold specifications to address the concern that the results of the analysis can be materially affected by the threshold used to estimate the firm-year portfolios' discount rate. Determining a reasonable threshold is important in this analysis, because two sources of bias can potentially affect the discount rate estimate. First, the projects' expected IRR are obtained using a noisy measure of the managers' *true* expectations. Figure 9 provides a graphical illustration of the effects of measurement noise on the observed firm-year portfolio's expected IRR distribution. For this reason, observations situated on the very left portion of the distribution proxy for the discount rate with measurement error. Thus, it is reasonable to extend the discount rate threshold slightly beyond the minimum value of the distribution. Second, taking value too far on the right side of the distribution would fail to capture the features associated with the discount rate, as it would more likely capture dynamics associated with the firm's average profitability and its opportunity set. Table XVII presents the main results with two alternative threshold specifications, to show that the results are robust. Columns 1 to 3 present the results using only the lowest bound of the expected IRR distribution, and columns 4 to 6 present the results using the observations in the 2.5th lowest percentile of the distribution.

G. Results by Time Period

Finally, I verify that managers price idiosyncratic risk consistently period by period. Precisely, Table XVIII reports the results for the price of idiosyncratic risk, evaluated per decade (i.e., [1983-1990), [1990-2000), [2000-2010]). The table shows that managers consistently adjust their discount rate to account for idiosyncratic risk, across the three decades. This indicates that the main specification results are not driven by specific events associated with one particular time period. Rather, the effect is economically significant across all three decades.

It is interesting to note that the price of idiosyncratic risk has been steadily declining over time, across all regression specifications. Although the goal of this paper is not to explain the time

trend for the price of idiosyncratic risk, future research investigating the underlying drivers of such phenomenon would be interesting.

IX. Conclusion

Choosing discount rates for new investment projects is a fundamental topic in corporate finance, yet we have almost no evidence on how managers make these choices in practice. This study helps fill this gap by analyzing the relation between projects' idiosyncratic risk and firms' project-specific discount rates. The primary findings are that (i) managers adjust their discount rates upward when faced with increased idiosyncratic risk; (ii) pricing idiosyncratic risk is negatively related to several measures of firm performance; (iii) managers appear to adjust their discount rate calculation to account for their exposure to undiversified unhedgeable risk, when facing costly external financing; and (iv) capital budgeting policies, and specifically the size of managers' budget, appear to provide firm owners with an additional lever to adjust managers' effective risk tolerance to desired levels.

An interesting implication of these results relates to the role of alternative tools for aligning managers' preferences. Most of the theoretical and empirical work in finance focuses on compensation contracts as the main means of insuring managers against the potential negative outcomes of specific projects. Echoing the theoretical insights provided by Holmstrom and Costa (1986), this analysis finds that capital budgeting policies, such as the size of managers' budget, can supplement contracts and other tools, and may even help to achieve this goal more efficiently.

Appendix A. Variable Definition

In this appendix, I define how each variable discussed in the paper is constructed. Subscript i corresponds to a specific firm, t corresponds to the year, j indicates a specific well, f refers to a region (i.e., a field or a state), p refers to a township, and k refers to the two portfolios at the firm-year level sorted on the idiosyncratic risk. A subscript with a minus sign, such as X_{-i} , indicates that the firm's own observations are excluded from the observations used in the calculation of the specific variable.

Appendix A.1. Gas Well Variables

1. # of Wells in a Township-Year: $N_{p,t}^j$ = Count the number of projects per township p and year t
2. # of Active Regions: $N_{i,t}^f$ = Count the number of fields or states the firm is active in during the year
3. # of Projects per Firm-Year Portfolio: $N_{i,t,k}^j$ = Count the number of projects per firm i , year t , and portfolio k
4. $Cost_j$ = The drilling cost of well j
5. Township-Year Average Well's Cost $Cost_{p,t} = \frac{\sum_{p,t} Cost_j}{N_{p,t}^j}$
6. $Asset_{i,t} = \sum_i Cost_j$, for all producing wells on year t for firm i
7. $Budget_{i,t} = \sum_{i,t} Cost_j$, for all the wells drilled on year t for firm i
8. Managers' Budget $Budget_{f,i,t} = \sum_{f,i,t} Cost_j$, for all the wells drilling on year t for firm i in region (i.e., field or state) f
9. Average Managers' Budget at the Firm Level $Budget_{i,t,f} = \frac{\sum_{i,t} Managers' Budget_{i,t,f}}{N_{i,t}^f}$
10. Natural Gas Price $P_t = P_t$
11. Operational Cost (%) = OP
12. Royalty Rate R_t (%) = R_t
13. Yearly Gas Production $Q_{i,t}$ (in 1,000 cf) = $Q_{i,t}$
14. Operating profit $Profit_{i,t} = P_t Q_{i,t} * (1 - R_t - OP) - Budget_{i,t}$
15. Gross Profit Margin $Margin_{i,t}$ (%) = $\frac{Operating Profit_{i,t}}{P_t Q_{i,t}} * 100$
16. Gross Profitability $Profitability_{i,t}$ (%) = $\frac{Operating Profit_{i,t}}{Asset_{i,t}} * 100$
17. Assets Growth $Growth_{i,t+1}$ (YoY) (%) = $\frac{Asset_{i,t+1}}{Asset_{i,t}} * 100$
18. Investment Rate $Rate_{i,t+1}$ (%) = $\frac{Budget_{i,t+1}}{Asset_{i,t}} * 100$
19. Discount Rate: $DR_{i,t,k}$ = Lower *region* of the firm-year portfolio's expected IRR distribution.
20. Project's Productivity Shock: $\zeta_j = \frac{\sum_{m=1}^{m=12} E[p_t] * q_{j,m} - \sum_{m=1}^{m=12} E[p_t] E[q_{j,m}]}{Cost_j}$
21. Township-Year Idiosyncratic Risk: $IR_{k,t} = \frac{1}{N_{p,t}^j - 1} \sum_{p,t} (\zeta_j - \bar{\zeta}_{p,t})^2$

22. Projects' Average Idiosyncratic Risk: Average $IR_{i,t,k} = \frac{1}{N_{i,t,k}^j} \sum_{i,t,k} IR_{k,t}$
23. Price of Idiosyncratic Risk $i,t = \frac{DR_{i,t,High} - DR_{i,t,Low}}{\text{Average } IR_{i,t,High} - \text{Average } IR_{i,t,Low}}$, where High and Low corresponds to the two firm-year portfolios sorted on the exposure to idiosyncratic risk
24. Largest Peers' Projects' Idiosyncratic Productivity Shock: Max Peer $IPS_{p,t} = \max_{p,t}[\zeta_{-j}]$
25. Average Largest Peers' Projects' Idiosyncratic Productivity Shock $i,t,k = \frac{1}{N_{i,t,k}^j} \sum_{i,t,k} \text{Max Peer } IR_{p,t}$
26. Annual Firm's Budget Diversification $i,t = \frac{N_{i,t}^j - 1}{\sum_{i,t} (\zeta_j - \zeta_{i,t})^2}$

Appendix A.2. Financial Market Variables

For the regressions using Compustat variables or other financial market variables, the variable definitions are below. Names are denoted by their Xpressfeed mnemonic in bold, when available.

1. Total Book Assets = **at**
2. Total Debt = **dltt + dlc**
3. Market Value of Equity: $MVE_{i,t} = \text{pstk} + \text{csho} * \text{prcc}_c$
4. Market Leverage = $\frac{\text{Total Debt}_{i,t}}{MVE_{i,t} + \text{Total Debt}_{i,t}}$
5. β_t^{OG} = One year CAMP Oil and Gas Industry beta, computed at the monthly frequency.
6. Risk-free Rate: $rf_t = 10\text{-year risk-free rate from St-Louis Federal Reserve.}$
7. Industry Cost of Equity: $r_t^E = rf_t + \beta_t^{OG} * (E(\frac{E_t}{P_t}) - rf_t)$
8. Cost of Debt: $r_{i,t}^D = \text{Interest rate of trading bonds from firms of equivalent credit rating.}$
9. Weighted Average Cost of Capital: $WACC_{i,t} = \frac{MVE_{i,t}}{MVE_{i,t} + \text{Total Debt}_{i,t}} * r_t^E + \frac{\text{Total Debt}_{i,t}}{MVE_{i,t} + \text{Total Debt}_{i,t}} * r_{i,t}^D$
10. Cash Flow: $CF = \frac{\text{oanfc} + \text{intpn}}{\text{at}}$
11. TLTD = $\frac{\text{dltt} + \text{dlc}}{\text{at}}$
12. TDIV = $\frac{\text{dvp} + \text{dvc}}{\text{at}}$
13. CASH = $\frac{\text{che}}{\text{at}}$
14. Market-to-book Ratio: $Q = \frac{MVE + \text{Total Debt} - \text{txditc}}{\text{at}}$
15. DIVPOS = is indicator that equals one if the firm pays dividends, and zero otherwise.
16. LNTA = $\ln(\text{at})$
17. Three-digit Industry YoY Sales Growth: $ISG = \frac{\sum_{\text{3 digit SIC}} \text{sale}_{i,t+1}}{\sum_{\text{3 digit SIC}} \text{sale}_{i,t}}$
18. Own-firm Real Year-over-Year (YoY) Sales Growth: $SG = \frac{\text{Real sale}_{i,t+1}}{\text{Real sale}_{i,t}}$
19. CURAT = $\frac{\text{act}}{\text{lct}}$
20. COVER = $\frac{\text{oibdp} - \text{dp}}{(\text{xint} + \text{dvp}) / (1 - \tau_c)}$, where τ_c is the tax rate.
21. IMARG = $\frac{\text{ni}}{\text{sale}}$
22. SLACK = $\frac{\text{che} + 0.5 * \text{inv} + 0.7 * \text{rect} - \text{dlc}}{\text{ppent}}$

Appendix A.3. Costly external financial variables

In the paper, I use four indexes to proxy for the level of costly external financing by firms. To construct each of the first three proxies (Cleary Index, Whited-Wu Index, Kaplan-Zingales index), I process the data following the methodology presented in Hennessy and Whited (2007). Finally, for each index to have the same interpretation, I follow the recommendation of Hennessy and Whited (2007) and multiply the Cleary index by -1 , such that it is increasing with the likelihood of facing costly external finance. Finally, to construct the Hadlock-Pierce index, I follow the methodology presented in Hadlock and Pierce (2010).

The indexes are constructed in the following way:

$$\begin{aligned} \text{Kaplan-Zingales index} = & -1.001909 * CF + 3.139193 * TLTD - 39.36780 * TDIV \\ & - 1.314759 * CASH + 0.2826389 * Q \end{aligned} \quad (10)$$

$$\begin{aligned} \text{Whited-Wu index} = & -0.091 * CF - 0.062 * DIVPOS + 0.021 * TLTD - 0.044 * LNNTA \\ & + 0.102 * ISG - 0.035 * SG \end{aligned} \quad (11)$$

$$\begin{aligned} \text{Cleary index} = & -0.11905 * CURAT - 1.903670 * TLTD + 0.00138 * COVER \\ & + 1.45618 * IMARG + 2.03604 * SG - 0.04772 * SLACK \end{aligned} \quad (12)$$

$$\text{Hadlock-Pierce index} = -0.737 * \log(\text{Asset}_{2004}) + 0.043 * \log(\text{Asset}_{2004})^2 + 0.040 * \text{Age} \quad (13)$$

Where *Age* is measured using the year in which a firm drills its first well in the *DrillingInfo* raw data sample, which starts in 1885.

Appendix B. Linearized ARP model

To estimate the Arp model using a OLS regression, I linearize the equation such that:

$$q_{j,m} = A_j(1 + b\theta m)^{\frac{-1}{b}} \quad (14)$$

$$\ln(q_{j,m}) = \ln(A_j) - \frac{1}{b}\ln(1 + b\theta m) \quad (15)$$

$$\ln(q_{j,m}) = \alpha_0 + \alpha_1 + A_j + \sum_{k=1}^K \beta_k m^k \quad (16)$$

Where the last step is obtained by doing a Taylor expansion of the term $\ln(1 + b\theta m)$. For a fixed m sufficiently small, the expansion terms converge to zero, since the product of b and θ is close to zero. In other words, I can approximate the hyperbolic decline curve using a K^{th} order polynomial. Finally, I include two dummy variables, α_0 and α_1 , equal to 1 for the first and second month of the well's production and zero otherwise, to account for the well's production ramp-up patterns (Dennis, 2017).

Appendix C. Well's Differential Exposure to Systematic Risk Factors

Wells in my analysis could have different exposure to some *potential* systematic risk factors (e.g., natural gas prices). For example, wells with a greater level of idiosyncratic risk are associated with a greater discount rate, for a given firm-year. Consequently, it is reasonable to expect that, on average, more risky wells produce larger quantities of natural gas than their smaller counterparts, all things being equal. Empirically, the correlation between wells' level of idiosyncratic risk and their associated level of production is 0.2. Now, wells producing greater quantities of natural gas are mechanically more exposed to natural gas prices, a potential systematic risk factor. This relationship can potentially alter how I interpret this study's core result, since it would imply that wells with a greater level of idiosyncratic risk are probably more exposed to systematic risk factors (i.e., natural gas prices), confounding idiosyncratic and systematic risk factors.

To illustrate how wells with different production levels could have a different exposure to natural gas prices, I use a simple example, such that:

$$p_z * q_{j,z,m} = \beta_{Well'sPriceExposure} p_z + \epsilon_{j,z,m} \quad (17)$$

Where p_z corresponds to the price of natural gas at time z , and $q_{j,z,m}$ is well j production at age m (in months). We can then derive the expression for the coefficient $\beta_{Well'sPriceExposure}$, such that:

$$\beta_{Well'sPriceExposure} = \frac{cov(p_z * q_{j,z,m}; p_z)}{var(p_z)} \quad (18)$$

$$= \frac{\mathbb{E}[p_z^2 * q_{j,z,m}] - \mathbb{E}[q_{j,z,m} * p_z] * \mathbb{E}[p_z]}{var(p_z)} \quad (19)$$

$$= \frac{\mathbb{E}[q_{j,z,m}](\mathbb{E}[p_z^2] - \mathbb{E}[p_z]^2)}{var(p_z)} \quad (20)$$

$$= \mathbb{E}[q_{j,z,m}] \quad (21)$$

Where I use the fact that wells' production flow is independent from the natural gas price process to obtain equation 19. Section IV provides an expansive discussion and some empirical support in favor of this assumption. This simple framework confirms the intuition that wells with a greater level of production flow may be more exposed to natural gas prices. This can potentially confound the *true* effect of idiosyncratic risk in the main analysis.

That being said, the quantity of risk is not the only relevant aspect to consider in this scenario. The price of this *potential* systematic risk factor is equally important in characterizing the consequence of a different exposure to systematic risk. There exists mixed evidence on the size of a natural gas risk premium or, to a more general extent, the risk premium of an *energy* factor. First, from a CAPM standpoint, the risk premium of natural gas is virtually zero³³. The sample average one-year CAPM monthly beta coefficient for natural gas is 0.004. Computing the measure over alternative horizons does not significantly alter the resulting coefficients such that the two-year horizon beta coefficient is 0.003, the three-year beta is 0.003, and the four-year beta is 0.003. Second, when looking at other asset pricing models, such as models derived from the arbitrage pricing theory (APT), there exists little consensus for the existence of an *energy* factor priced by the market. On one side, Chen et al. (1986) and Kilian and Park (2009), among others, find little evidence in favor of an energy factor. Chen et al. (1986) find that oil price risk is not separately valued in the stock market, while Kilian and Park (2009) find limited explanatory power for oil supply and demand shocks in explaining stock returns. On the other side, Chiang et al. (2014) and Ready (2017) provide evidence in favor of an energy factor priced by the market.

Given the lack of general agreement in academic research for the existence of a priced energy risk factor, I include the wells' differential exposure to this *potential* systematic risk factor in my main specification. To do so, I use the results derived in equation 21. Precisely, for each firm-year portfolio, I measure the average production of the wells that were drilled, to proxy for their average exposure to natural gas prices.

³³Berk and van Binsbergen (2016) provide empirical evidence suggesting that the representative investor utilizes the CAPM to determine the risk premium.

Appendix D. Sign of the Endogeneity Bias

To guide the analysis of the endogeneity bias sign in the reduced-form regression, it is useful to look at a simple regression case to work within an intuitive framework. For illustration's sake, one can take the example that managers with different level of experience might not be randomly allocated among the two firm-year portfolios (i.e., the high and low idiosyncratic risk portfolios), such that *Managers' Experience* would be part of the *true* data generating process:

$$\text{Discount Rate}_{i,t,k} = \beta_1 \text{Idiosyncratic Risk}_{i,t,k} + \beta_2 \text{Managers' Experience}_{i,t,k} + \epsilon_{i,t,k} \quad (22)$$

In the case where *Managers' Experience* is omitted from the *true* regression model, the reduced-form regression would then be:

$$\text{Discount Rate}_{i,t,k} = \beta_1^* \text{Idiosyncratic Risk}_{i,t,k} + \epsilon(\text{Managers' Experience})_{i,t,k} \quad (23)$$

In this simplified example, the expression of the *biased* reduced-form β_1^* can be defined as:

$$\beta_1^* = \beta_1 + \beta_2 \frac{\text{cov}(\text{Idiosyncratic Risk}_{i,t,k}; \text{Managers' Experience}_{i,t,k})}{\text{var}(\text{Idiosyncratic Risk}_{i,t,k})} \quad (24)$$

From this simple example, one can note that the direction of the bias for the coefficient of interest (β_1^*) depends on (i) the covariance between the managers' experience and the level of idiosyncratic risk associated with the wells, and (ii) β_2 , the linear relationship between managers' experience and the firms' discount rate.

Appendix E. Revealed Preference Strategy with Real Option

To account for the real option effect, I adjust the firms' decision rule, such that I no longer assume that it is optimal to invest when the expected discounted cash flows of the wells are greater than the cost (C_j), but I assume that the wells are exercised when the discounted cash flows are greater than the real option optimal threshold (V_j^*), such that:

$$\sum_{m=1}^M \frac{1}{(1 + \mu_j)^m} \mathbb{E}[q_{j,m}] \mathbb{E}[P_j] - V_j^* = 0 \quad (25)$$

To compute the real option optimal threshold (V_j^*), I follow the methodology introduced in Dixit and Pindyck (1996, Chapter 5) such that:

$$V_j^* = \frac{\beta_j^1}{\beta_j^1 - 1} * C_j \quad (26)$$

$$\beta_j^1 = \frac{1}{2} - \frac{r_t - \delta}{\sigma_j^2 + \omega_t^2} + \sqrt{\left[\frac{(r_t - \delta)}{\sigma_j^2 + \omega_t^2} - \frac{1}{2}\right]^2 + \frac{2r_t}{\sigma_j^2 + \omega_t^2}} \quad (27)$$

where C_j denotes the well's drilling cost, r denotes the 10-year risk-free rate, δ corresponds to the project's dividend rate, σ_j^2 is the project's idiosyncratic risk, and ω_t^2 is the natural gas risk.

I follow Brennan and Schwartz (1985) and set the dividend rate (i.e., δ) equal to the natural gas convenience yield. I compute the convenience yield using the natural gas spot and Bloomberg Natural Gas Future prices. Precisely, I obtain the sample average natural gas convenience yield (i.e., δ) such that:

$$\delta = \frac{1}{11} \sum_{t=2000}^{2010} \left[r_t + \frac{1}{3} \left(1 - \frac{F_t}{S_t} \right) \right] \quad (28)$$

Where t is the year during which the convenience yield is measure, F_t is the Bloomberg three-year Natural Gas Future Price, and S_t is the spot price.

Finally, I define the project's risks as the combination of the project's idiosyncratic risk (σ_j^2) and price risk (ω_t^2). The project's idiosyncratic risk is the same measure as the one I use throughout the paper. The measure of price risk corresponds to the three-year Bloomberg Natural Gas Futures contract implied volatility. Kellogg (2014) has an extensive discussion on which measure of price uncertainty is best to use in a real option calibration, and concludes that using implied volatility

derived from financial derivatives is optimal. However, the financial option for the three-year horizon contracts are not available on Bloomberg before 2000. For this reason, the number of observations used in the regression of this section is smaller than that of the main specification.

REFERENCES

- Daron Acemoglu, Philippe Aghion, Claire Lelarge, John van Reenen, and Fabrizio Zilibotti. Technology, information, and the decentralization of the firm. *The Quarterly Journal of Economics*, 2007.
- Philippe Aghion and Jean Tirole. Formal and real authority in organizations. *Journal of Political Economy*, 1997.
- Anup Agrawal and Gershon N. Mandelker. Managerial incentives and corporate investment and financing decisions. *The Journal of Finance*, 1987.
- Soren T. Anderson, Ryan Kellogg, and Stephen W. Salant. Hotelling under pressure. *Journal of Political Economy*, 2018.
- Andrew Ang, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. High idiosyncratic volatility and low returns: International and further u.s. evidence. *Journal of Financial Economics*, 2009.
- Christopher S. Armstrong and Rahul Vashishtha. Executive stock options, differential risk-taking incentives, and firm value. *Journal of Financial Economics*, 2012.
- Lucian A. Bebchuk and Holger Spamann. Regulating bankers' pay. *The Georgetown Law Journal*, 2010.
- Jonathan B. Berk and Jules H. van Binsbergen. Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 2016.
- Nick Bloom, Stephen Bond, and John Van Reenen. Uncertainty and investment dynamics. *Review of Economic Studies*, 2007.
- Marcus C. Bogue and Richard Roll. Capital budgeting of risky projects with "imperfect" markets for physical capital. *The Journal of Finance*, 1974.
- Douglas R. Bohi. Changing productivity in u.s. petroleum exploration and development. *Charles River Associates*, 1998.

- Patrick Bolton, Jose Scheinkman, and Wei Xiong. Executive compensation and short-termist behaviour in speculative markets. *The Journal of Finance*, 2006.
- Patrick Bolton, Hui Chen, and Neng Wang. A unified theory of tobins q, corporate investment, financing, and risk management. *The Journal of Finance*, 2011.
- Richard A. Brealey and Stewart C. Myers. Principles of corporate finance, seventh edition. *McGraw Hill Publisher*, 1996.
- Michael J. Brennan and Eduardo S. Schwartz. Evaluating natural resource investments. *The Journal of Business*, 1985.
- Eve Caroli and John Van Reenen. Skill-biased organizational change? evidence from a panel of british and french establishments. *The Quarterly Journal of Economics*, 2001.
- Nai-Fu Chen, Richard Roll, and Stephen A. Ross. Economic forces and the stock market. *The Journal of Business*, 1986.
- Judith Chevalier and Glenn Ellison. Career concerns of mutual fund managers. *The Quarterly Journal of Economics*, 1999.
- I-Hsuan Ethan Chiang, W. Keener Hughen, and Jacob S. Sagi. Estimating oil risk factors using information from equity and derivatives markets. *The Journal of Finance*, 2014.
- Jeffrey L. Coles, Naveen D. Daniel, and Lalith Naveen. Managerial incentives and risk-taking. *Journal of Financial Economics*, 2006.
- Massimo G. Colombo and Marco Delmastro. Delegation of authority in business organizations: An empirical test. *The Journal of Industrial Economics*, 2004.
- George M. Constantinides. Market risk adjustment in project valuation. *The Journal of Finance*, 1978.
- Joshua D. Coval and Tobias J. Moskowitz. Home bias at home: Local equity preference in domestic portfolios. *Journal of Finance*, 1999.
- Joshua D. Coval and Tobias J. Moskowitz. The geography of investment: Informed trading and asset prices. *Journal of Political Economy*, 2001.

- Thomas R. Covert. Experiential and social learning in firms: The case of hydraulic fracturing in the bakken shale. *Working Paper*, 2015.
- Paul H. Decaire, Erik P. Gilje, and Jrme P. Taillard. Real option exercise: Empirical evidence. *Review of Financial Studies*, 2019.
- Rebecca S. Demsetz and Philip E. Strahan. Diversification, size and risk at u.s. bank holding companies. *Journal of Money, Credit and Banking*, 1997.
- Michael Dennis. Developing synthetic reservoir type curve model for use in evaluating surface facility and gathering pipe network designs. *Journal of Natural Gas Science & Engineering*, 2017.
- Douglas W. Diamond. Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 1984.
- Avinash K. Dixit and Robert S. Pindyck. *Investment under Uncertainty*. Princeton University Press, 1996.
- Zhiyong Dong, Cong Wang, and Fei Xie. Do executive stock options induce excessive risk taking? *Journal of Banking and Finance*, 2010.
- Eugene F. Fama and Kenneth R. French. The equity premium. *The Journal of Finance*, 2002.
- Steven M. Fazzari and Bruce C. Petersen. Working capital and fixed investment: New evidence on financing constraints. *The RAND Journal of Economics*, 1993.
- Michael Fetkovich. Useful concepts for decline curve forecasting, reserve estimation, and analysis. *SPE Reservoir Engineering*, 1996.
- Kenneth A. Froot, David S. Scharfstein, and Jeremy C. Stein. Risk management: Coordinating corporate investment and financing policies. *The Journal of Finance*, 1993.
- Huasheng Gao, Jarrad Harford, and Kai Li. Determinants of corporate cash policy: Insights from private firms. *Journal of Financial Economics*, 2013.
- John Geanakoplos and Paul Milgrom. A theory of hierarchies based on limited managerial attention. *Journal of the Japanese and International Economies*, 1991.

Erik Gilje and Jerome Taillard. Do private firms invest differently than public firms? taking cues from the natural gas industry. *Journal of Finance*, 2016.

Xavier Giroud. Proximity and investment: Evidence from plant-level data. *The Quarterly Journal of Economics*, 2013.

Todd A. Gormley, David A Matsa, and Todd T. Milbourn. Ceo compensation and corporate risk-taking: Evidence from a natural experiment. *Journal of Accounting and Economics*, 2013.

Amit Goyal and Pedro Santa-Clara. Idiosyncratic risk matters! *The Journal of Finance*, 2003.

John R. Graham and Campbell R. Harvey. The theory and practice of corporate finance: evidence from the field. *Journal of Financial Economics*, 2001.

John R. Graham, Campbell R. Harvey, and Manju Puri. Capital allocation and delegation of decision-making authority within firms. *Journal of Financial Economics*, 2015.

William H. Greene. *Econometric Analysis (Fifth ed.)*. Prentice-Hall, 2003.

Wayne R. Guay. The sensitivity of ceo wealth to equity risk: an analysis of the magnitude and determinants. *Journal of Financial Economics*, 1999.

Charles J. Hadlock and Joshua R. Pierce. New evidence on measuring financial constraints: Moving beyond the kz index. *The Review of Financial Studies*, 2010.

Jens Hagendorff and Francesco Valsancas. Ceo pay incentives and risk-taking: Evidence from bank acquisitions. *Journal of Corporate Finance*, 2011.

Christopher A. Hennessy and Toni M. Whited. How costly is external financing? evidence from a structural estimation. *The Journal of Finance*, 2007.

Evan Herrnstadt, Ryan Kellogg, and Eric Lewis. Royalties and deadlines in oil and gas leasing: Theory and evidence. *Working Paper*, 2019.

Charles Hodgson. Information externalities, free riding, and optimal exploration in the uk oil industry. *Working paper*, 2019.

- Bengt Holmstrom and Joan Ricart I Costa. Managerial incentives and capital management. *The Quarterly Journal of Economics*, 1986.
- Bengt Holmstrom and Laurence Weiss. Managerial incentives, investment and aggregate implications: Scale effects. *The Review of Economic Studies*, 1985.
- Michael T. Jacobs and Anil Shivdasani. Do you know your cost of capital? *harvard Business Review*, 2012.
- Ravi Jagannathan, David A. Matsa, Iwan Meier, and Vefa Tarhan. Why do firms use high discount rates? *Journal of Financial Economics*, 2016.
- Ryan Kellogg. Learning by drilling: Interfirm learning and relationship persistence in the texas oilpatch. *The Quarterly Journal of Economics*, 2011.
- Ryan Kellogg. The effect of uncertainty on investment: Evidence from texas oil drilling. *American Economic Review*, 2014.
- Lutz Kilian and Cheolbeom Park. The impact of oil price shocks on the u.s. stock market. *International Economic Review*, 2009.
- Philipp Kruger, Augustin Landier, and David Thesmar. The wacc fallacy: The real effects of using a unique discount rate. *The Journal of Finance*, 2015.
- Richard A. Lambert. Executive effort and selection of risky projects. *The RAND Journal of Economics*, 1986.
- Kewen Li and Roland N. Horne. A decline curve analysis model based on fluid flow mechanisms. *Society of Petroleum Engineers*, 2003.
- Evgeny Lyandres. Costly external financing, investment timing, and investment-cash flow sensitivity. *Journal of Corporate Finance*, 2007.
- Tianshou Ma, Ping Chen, and Jian Zhao. Overview on vertical and directional drilling technologies for the exploration and exploitation of deep petroleum resources. *Springer International Publishing*, 2016.

Robert C. Merton. On the pricing of corporate debt: the risk structure of interest rates. *The Journal of Finance*, 1974.

Merton H. Miller and Daniel Orr. A model of the demand for money by firms. *The Quarterly Journal of Economics*, 1966.

Stewart C. Myers and Stuart M. Turnbull. Capital budgeting and the capital asset pricing model: good news and bad news. *The Journal of Finance*, 1977.

M. P. Narayanan. Managerial incentives for short-term results. *The Journal of Finance*, 1985.

Vasia Panousi and Dimitris Papanikolaou. Investment, idiosyncratic risk, and ownership. *The Journal of Finance*, 2012.

James M. Poterba and Lawrence H. Summer. A ceo survey of u.s. companies' time horizons and hurdle rates. *Sloan Management Review*, 1995.

Shivaram Rajgopal and Terry Shevlin. Empirical evidence on the relation between stock option compensation and risk taking. *Journal of Accounting and Economics*, 2002.

Robert C. Ready. Oil prices and the stock market. *Review of Finance*, 2017.

Stephen A. Ross. The economic theory of agency: The principal's problem. *The American Economic Review*, 1973.

Amit Seru. Firm boundaries matter: Evidence from conglomerates and r&d activity. *Journal of Financial Economics*, 2014.

John Y. Campbell Glen B. Taksler. Equity volatility and corporate bond yields. *The Journal of Finance*, 2003.

Peter Tufano. Who manages risk? an empirical examination of risk management practices in the gold mining industry. *The Journal of Finance*, 1996.

Example of Horizontal and Vertical Wells

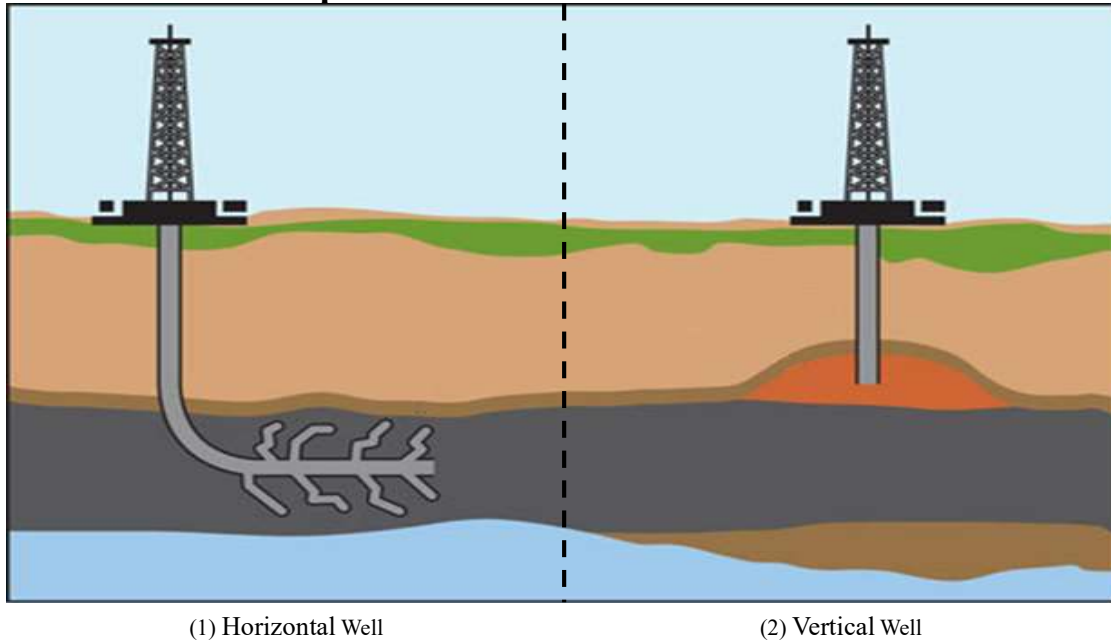


Figure 1: Vertical versus Horizontal Drilling Technology

This figure provides a graphical illustration of the difference between horizontal and vertical wells. Vertical wells represent the older technology, predominantly used in the first part of the American oil and gas development (i.e.; 1900-2005). During the analyzed period, 89% of the gas wells drilled in my sample were completed using the vertical technology.

Panhandle Field's Development from 1961 to 2010



Figure 2.1. 1961 map of approximate boundary of Panhandle oil and gas field producing region. Source: *Anderson and Hinson, 1961; Boone 1958; and G.B. Shelton, U.S. Bureau of Mines, written communication, 1958.*

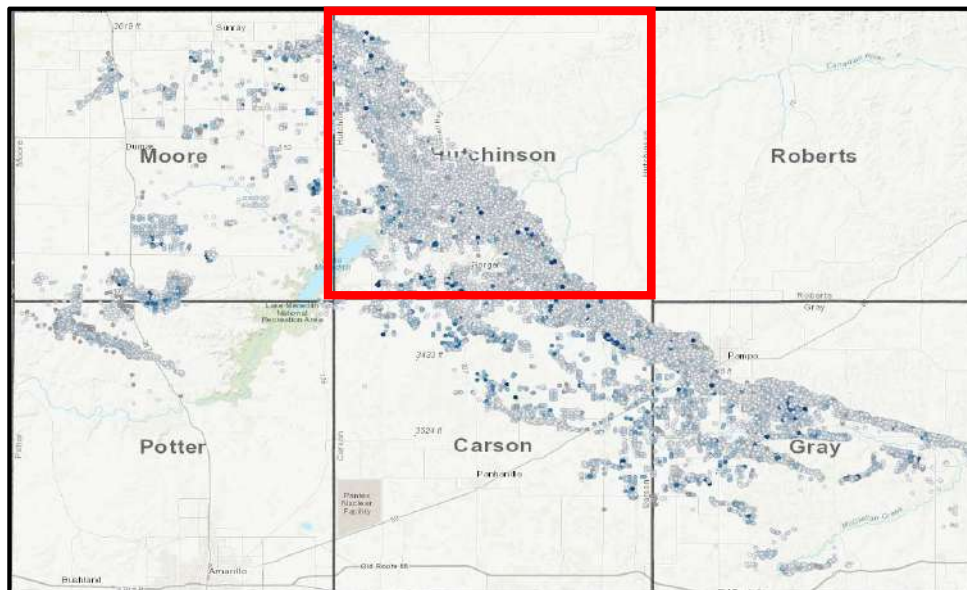


Figure 2.2. 2010 map of cumulative oil and gas wells drilled in the Panhandle field. Each dot represents an individual well. Wells' quality is indicated by a color code. Darker shade of blue indicates wells that were among the most productive of the region, while dots color coded in gray indicate lower level of productivity.

Figure 2. Panhandle Field (Texas) Development Progress between 1961-2010

This panel of figures plots the evolution of the Panhandle field development over the period 1961 to 2010. Figure 2.1. provides the initial expectation of the field boundary, based on geological surveys. Figure 2.2. provides an updated view of the field development. The red square indicates the Hutchinson county to help align the surveyor map with the 2010 map.

Excerpt from Energy Firms' 10-K Statement for Ongoing U.S. Activities

B. Review of Principal Ongoing Activities

UNITED STATES

ExxonMobil's year-end 2018 acreage holdings totaled 12.1 million net acres, of which 0.8 million net acres were offshore. ExxonMobil was active in areas onshore and offshore in the lower 48 states and in Alaska.

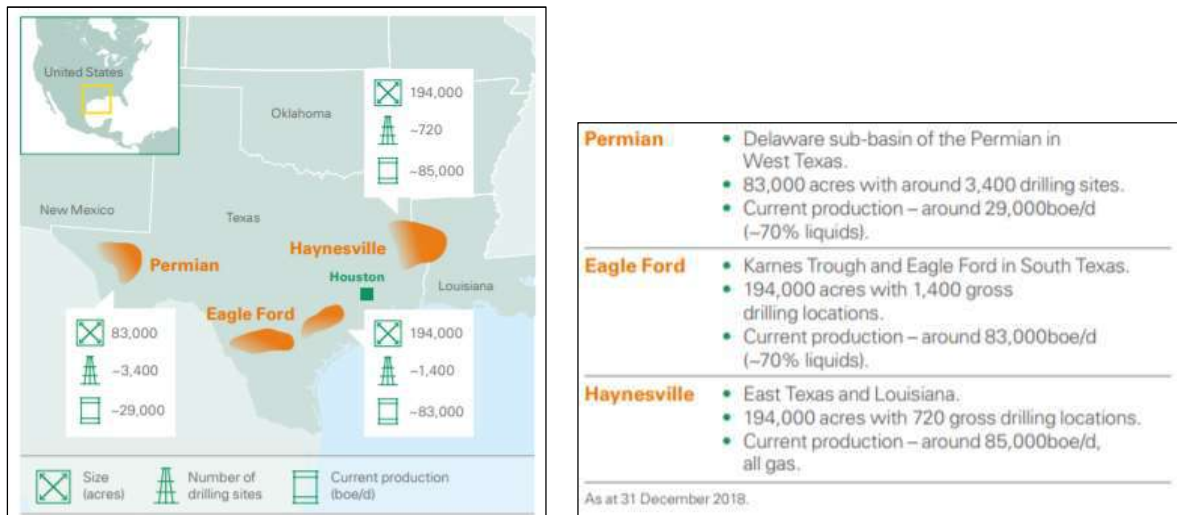
During the year, 554.6 net exploration and development wells were completed in the inland lower 48 states. Development activities focused on liquids-rich opportunities in the onshore U.S., primarily in the Permian Basin of West Texas and New Mexico and the Bakken oil play in North Dakota. In addition, gas development activities continued in the Marcellus Shale of Pennsylvania and West Virginia, the Utica Shale of Ohio and the Haynesville Shale of East Texas and Louisiana.

ExxonMobil's net acreage in the Gulf of Mexico at year-end 2018 was 0.7 million acres. A total of 3.5 net exploration and development wells were completed during the year.

Participation in Alaska production and development continued with a total of 7.3 net development wells completed.

Panel 3.1: U.S. Upstream Business of Exxon Mobil Corporation (2018).

This figure presents an example of how energy firms break down their exploration and production activities in the United-States. There is a strong focus on geographical detail, often referring to states or fields to define their upstream activities.



Panel 3.2: U.S. Upstream Business of British Petroleum Plc. (2018).

This figure presents how British Petroleum Plc. breaks down its upstream operations (i.e., exploration and production) in the United-States.

Figure 3: Energy Firms' Break Down of Upstream Activities

The figures in the two above panels present examples of how energy firms break down and discuss their activities. Those firms rely heavily on geographical boundaries to define their operations, referring to man-made boundaries (i.e., states) or naturally occurring ones (i.e., geological structure) in most cases.

Geographic Distribution of the Vertical Gas Wells

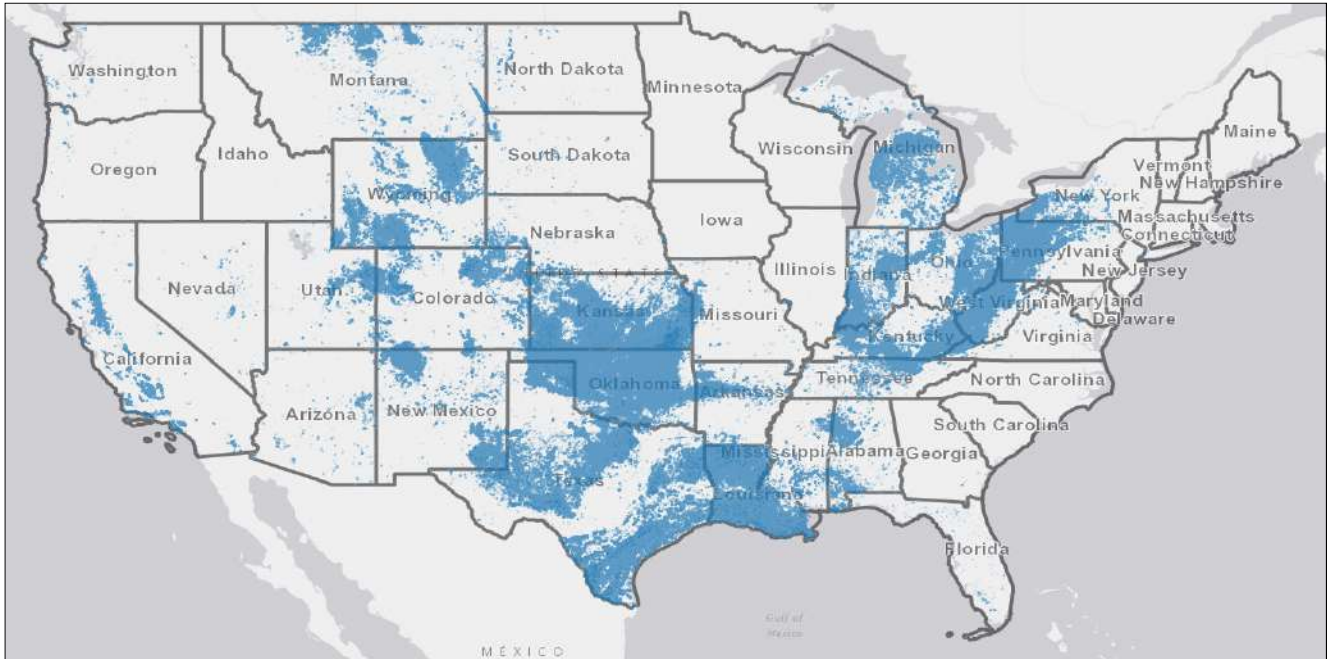


Figure 4: Projects Geographic Distribution

This figure plots the sample of wells included in the analysis. The total sample includes 114,696 vertical gas wells drilled over the period ranging from 1983 to 2010. The map provides information on the regions with the most activity during the analyzed period.

Expected and Realized Well's Production Decline Over Time

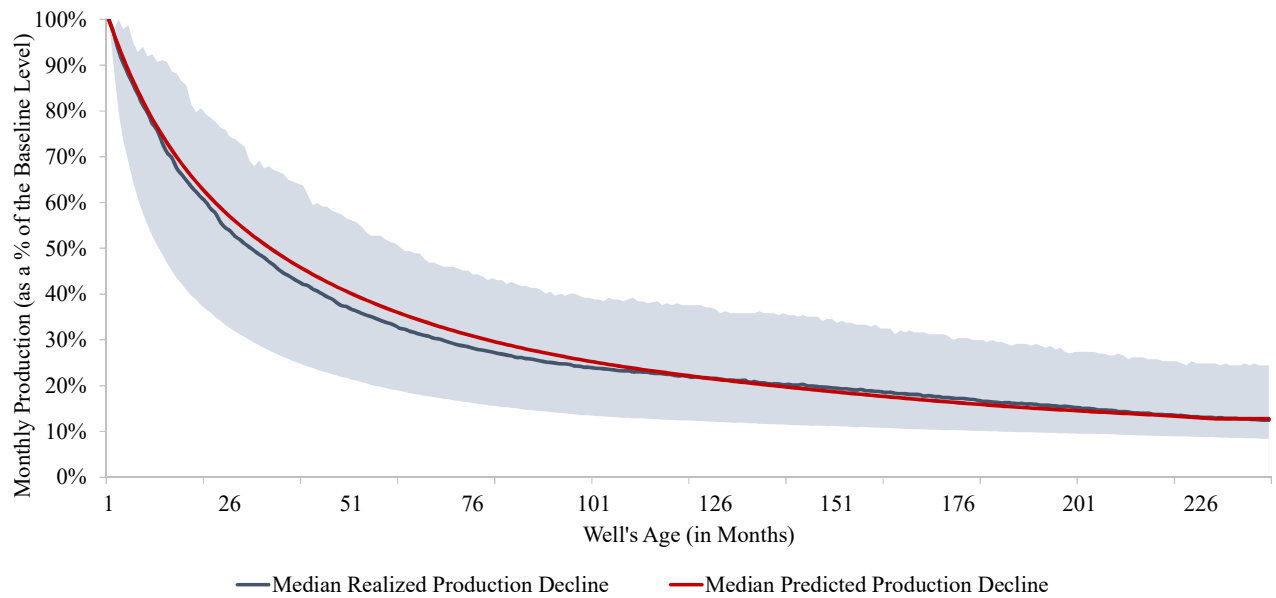


Figure 5: Arp Hyperbolic Production Curve

This figure plots the wells production decline level over time. The blue line corresponds to the median empirical production, the red line corresponds to the hyperbolic Arp prediction and the shaded area represent the 10th and 90th confidence interval.

Variables Constructed Using the Township-Year Idiosyncratic Productivity Shocks

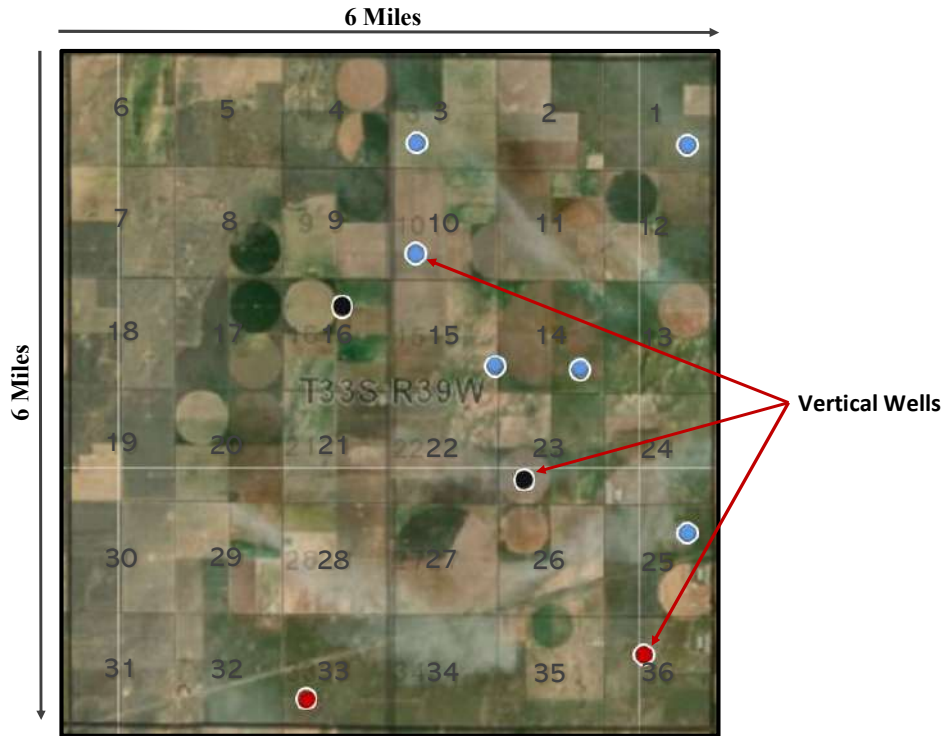


Figure 6.1. Bird Eye View of a Township-Year (Kansas)

This figure plots the wells drilled in the township (33S-39W) in Kansas, for the year 1990 to 1991. A township is a 6 miles by 6 miles square of land. In the Public Land Survey System, each township is constituted of 36 1-squared mile sections. The colored circles represent distinct wells drilled by the three active firms in the township-year (Occidental Petroleum, Linn Energy, and Merit Energy).

	Idiosyncratic Productivity Shocks (ζ)		
	Occidental Petroleum	Linn Energy	Merit Energy
	Red	Blue	Black
(ζ_1) Well 1	0.05	-0.22	0.23
(ζ_2) Well 2	-0.1	0.1	0.03
(ζ_3) Well 3		0.01	
(ζ_4) Well 4		0.12	
(ζ_5) Well 5		-0.04	
(ζ_6) Well 6		0.14	
Largest Peer's Idiosyncratic Productivity Shock	0.23	0.23	0.14
Projects' Idiosyncratic Risk: 0.129			

Figure 6.2: Realized Idiosyncratic Productivity Shocks, Idiosyncratic Risk, and Instrumental Variable

This table presents an example of the realized idiosyncratic productivity shocks for the wells drilled in the township-year, for the three active firms. Sigma (ζ) represents the wells' specific idiosyncratic shocks. For each well drilled in the township-year, I determine the well's level measure of idiosyncratic risk, *Projects' Idiosyncratic Risk*, as the cross-sectional standard deviation measured for the township-year (e.g., 0.129). Finally, the instrumental variable, *Largest Peers' Idiosyncratic Productivity Shock*, corresponds to the largest idiosyncratic shocks experienced by a firm's peers. For example, for the Red firm, the largest peers' idiosyncratic shock is 0.23, experienced by the Black firm.

Figure 6: Variables Constructed Using the Township-Year Idiosyncratic Productivity Shocks

Figure 6.1. presents a simplified example of wells being drilled in a given township-year. In this example, three firms (i.e., Red, Blue, and Black) were active in the township during that specific year. The adjacent table (Figure 6.2) reports an illustrative example of the potential idiosyncratic productivity shock, measured for each well. The instrumental variable used in the paper, *Average Largest Peers' Idiosyncratic Productivity Shock*, corresponds to the biggest shock that was measured for the firm's peers in its wells' township-year, averaged at the firm-year portfolio level. To obtain the *Projects' Average Idiosyncratic Risk*, I take the average value of *Projects' Idiosyncratic Risk* for each firm-year portfolio.

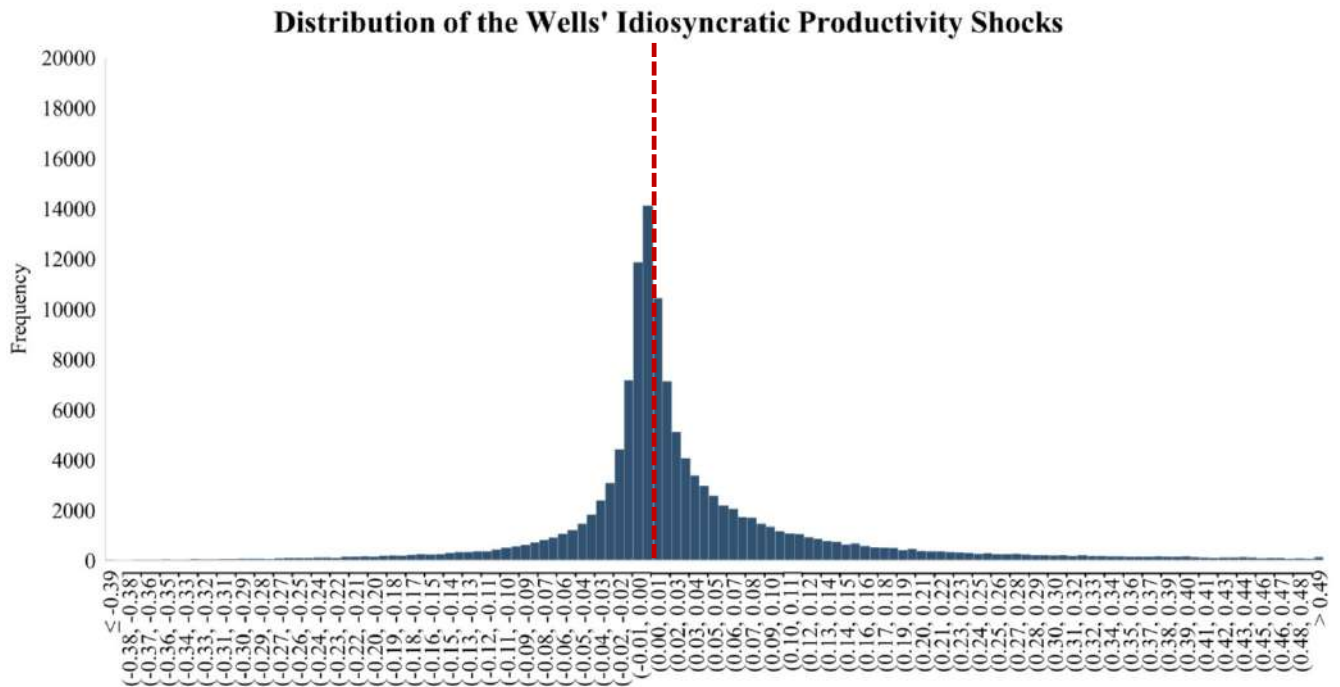


Figure 7: Wells' Idiosyncratic productivity Shocks

This figure plots the distribution of the well's idiosyncratic productivity shocks. The total sample includes 114,696 vertical gas wells drilled over the period ranging from 1983 to 2010. values to the right of the red dashed line indicate positive shocks, while value to the left indicate negative shocks.

Natural Gas Wellhead Price by Region over Time

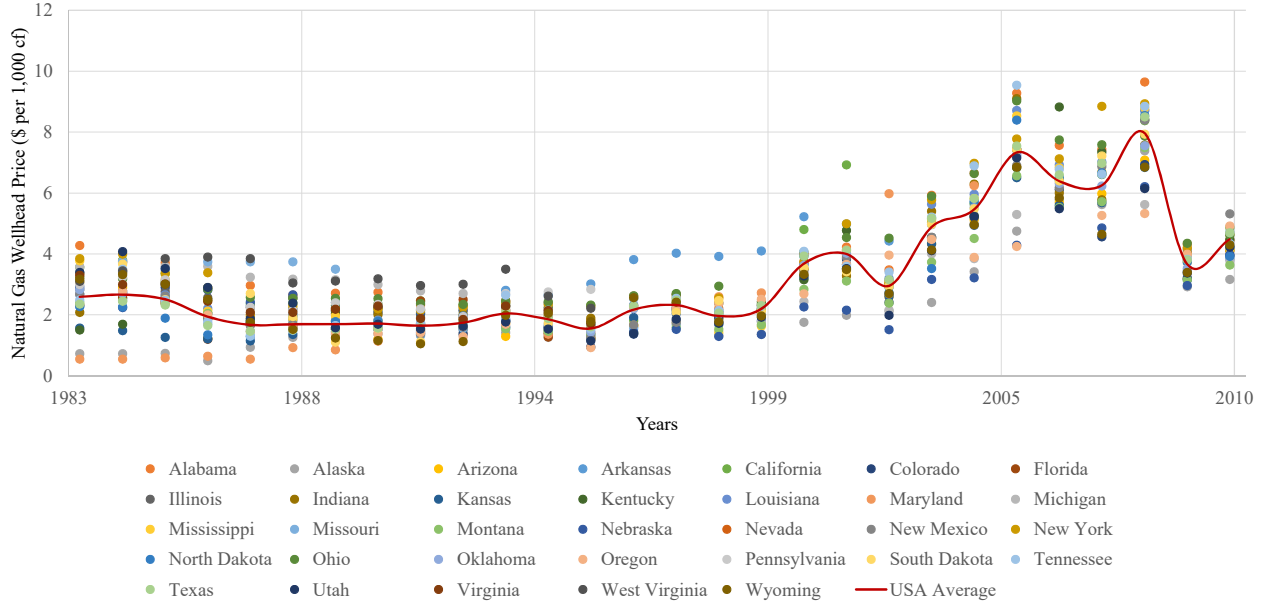


Figure 8: Natural Gas Wellhead Price by States between 1983 and 2010

This figure plots the evolution of yearly natural gas wellhead prices for each producing state over time. Source: https://www.eia.gov/dnav/ng/ng_prod_whv_a_EPG0_FWA_dpncf_a.htm

Firm-Year Portfolio's Projects' Expected IRR Distribution

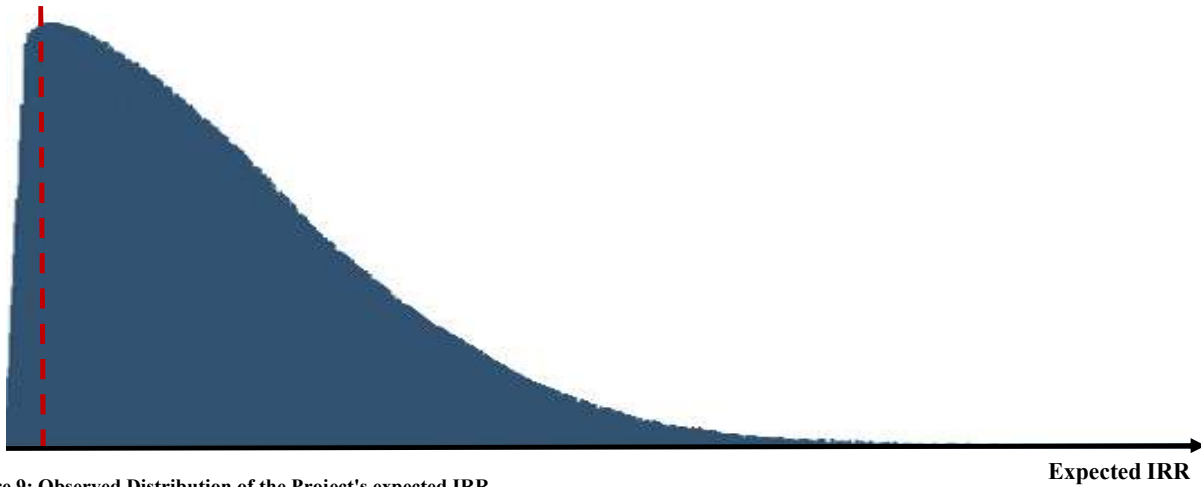


Figure 9: Observed Distribution of the Project's expected IRR

This figure plots the distribution of the projects' expected IRR for the firm-year portfolios. If there was no measurement error in the projects' expected IRR, the observed distribution would cut sharply at the red dotted line. However, because of measurement error in the projects' expected IRR, the tails of the distribution are fatter, and the left tail of the distribution extends beyond the firms *true* cut-off value.

Table I
Summary Statistics of Firms' and Wells' Characteristics

This table reports summary statistics of exploration and production gas companies included in the sample. The time period of the sample is from 1983 to 2010. The sample consists of all firms drilling at least 10 gas wells in the year of analysis, and wells drilled in township-year with at least 3 wells. I exclude from the analysis all wells with missing fields, and wells for which the first production date occurs before the drilling date, as they correspond to data entry error. Panel A reports summary statistics of the firm's characteristics. Panel B reports well-level characteristics used to estimate the Arp model.

	Observation	Mean	Median	Std. Dev.
Panel A: Firm Level Data				
Assets (In millions \$)	3,946	229.17	84.87	383.79
Annual Budget (In millions \$)	3,946	60.34	22.95	108.80
Annual Budget per Field (In millions \$)	3,946	11.30	6.07	17.57
Annual Budget per State (In millions \$)	3,946	19.37	10.30	30.09
Number of Firms	369			
	Observation	Mean	Median	Std. Dev.
Panel B: Well Level Data				
Drilling Cost (\$)	114,696	465,652.90	402,357.30	299,580.20
Drilling Cost (\$ per foot)	114,696	79.07	81.48	6.94
Royalty Rate (%)	114,696	17.32%	18.75%	2.83%
Operational Cost (%)	114,696	20.00%	20.00%	0.00%
Well Total Gas Production (in 1,000 cf)	114,696	570,049.90	177,654.50	1,608,979.00
EIA three-year forecast gas prices (Per 1,000 cf)	114,696	4.05	3.37	1.83

Table II
Firms' Discount Rate and The Cost of Capital

This table reports coefficient estimates from an OLS regression for the relation between the cost of capital and firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i , and year t level. The *Industry Cost of Equity* is calculated using the oil and gas industry beta, computed at the monthly frequency on a one-year horizon basis, multiplied by the expected market excess return. The oil and gas industry returns are obtained from Kenneth French web site. Market excess return is approximated using the earning-to-price ratio obtained from Robert Shiller web site. The risk-free rate is the 10-year risk-free rate, obtained from the St-Louis Federal Reserve website. Finally, to compute the *weighted average cost of capital* (WACC), I obtain the cost of debt using firms credit rating reported in Capital IQ. See appendix A.2 for the full methodological details. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%) _{i,t,k}			
	(1)	(2)	(3)	(4)
(β_1) WACC (%) _{i,t}	1.403*** [2.88]	1.549*** [2.80]	1.367*** [3.13]	1.325** [2.40]
(β_2) Project's Average Idiosyncratic Risk _{i,t,k}			11.862*** [3.06]	9.989** [2.43]
Firm Fixed Effect _i	No	Yes	No	Yes
R-Squared	0.011	0.298	0.152	0.383
F-Statistic	8.308	7.831	19.800	13.866
Observations	748	748	748	748

Table VIII
Year-over-Year Managers' Share of Firm's Budget Variation

This table reports coefficient estimates from an OLS regression for the managers' budget change YoY on the annual region's forecast dispersion, and t-statistics robust to heteroskedasticity, within-firm and within-region (i.e., field or state) dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i , year t , and region f level. The sample used in the below regression only includes observations from firms that were *active in more than one region* during the analyzed year. The variable Region's Forecast Dispersion denotes the standard deviation of a firm's wells' drilled in a specific region in a given year. The variable *Managers' Budget Change YoY* corresponds to the change in the managers' share of the firm's budget between two years. For example, a value of 5% would indicate that the firm's budget allocation to the manager's region increased by 5% YoY. The variable *Region's Forecast Dispersion* is scaled by its standard deviation to simplify the lecture of the table and facilitate the comparison between the two potential regions of assignment. Detailed calculation of the regression variables is available in appendix A.1. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Managers' Share of Firm's Budget Change YoY (%) _{<i>i,t+1,f</i>}							
	Managers' Budget (Region = Field)				Managers' Budget (Region = State)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(β_1) Region's Forecast Dispersion _{<i>i,t,f</i>}	-2.651 [-1.60]	-2.246 [-1.34]	-5.736** [-2.10]	-6.385* [-1.81]	-5.507* [-1.84]	-5.368* [-1.77]	-9.721** [-2.29]	-7.561* [-1.70]
(β_2) Assets _{<i>i,t</i>}	0.030 [1.05]	0.039 [1.31]			-0.001 [-0.03]	0.004 [0.09]		
(β_3) Budget _{<i>i,t</i>}	0.019 [1.56]	0.003 [0.23]			-0.003 [-0.17]	-0.001 [-0.02]		
Firm Fixed Effect _{<i>i</i>}	Yes	Yes	No	No	Yes	Yes	No	No
Year Fixed Effect _{<i>t</i>}	No	Yes	No	No	No	Yes	No	No
Firm-Year Fixed Effect _{<i>i,t</i>}	No	No	Yes	Yes	No	No	Yes	Yes
Region-Year Fixed Effect _{<i>i,t</i>}	No	No	No	Yes	No	No	No	Yes
R-Squared	0.09	0.11	0.49	0.54	0.04	0.05	0.23	0.25
F-Statistic	8.315	2.643	4.428	3.262	1.134	1.075	5.227	2.874
Observations	6,374	6,374	6,374	6,374	4,419	4,419	4,419	4,419

Table XIII**Managers' Project-Level Idiosyncratic Risk Pricing - Leverage Effect**

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i , year t , and portfolio k level. The *Leverage* variable corresponds to the firms' market leverage calculated using the firm 10-k annual statement and stock market data. Detailed calculations are available in appendix A.2. The analysis is restricted to the set of firms available in Compustat for which the necessary variables were available. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%) _{i,t,k}			
	(1)	(2)	(3)	(4)
(β_1) Projects' Average Idiosyncratic Risk _{i,t,k}	6.110** [2.53]	6.261** [2.53]	4.372** [2.13]	4.416** [2.04]
(β_2) Budget _{i,t}		-0.010 [-1.34]		
(β_3) Assets _{i,t}	0.002 [0.38]	0.008 [1.15]		
(β_4) Leverage _{i,t}	-6.581 [-1.25]	-5.588 [-1.06]		
(β_5) Leverage _{i,t} * Projects' Average Idiosyncratic Risk _{i,t,k}	6.459 [0.77]	6.184 [0.72]	17.000** [2.13]	17.319** [2.16]
(β_6) Average Natural Gas Production Level _{i,t,k}	0.371* [1.78]	0.368* [1.79]	0.313 [1.42]	0.322 [1.29]
Firm Fixed Effect _i	Yes	Yes	No	No
Year Fixed Effect _t	Yes	Yes	No	No
Firm-Year Fixed Effect _{i,t}	No	No	Yes	Yes
Portfolio Fixed Effect _k	No	No	No	Yes
R-Squared	0.644	0.631	0.828	0.828
F-Statistic	5.039	4.920	9.000	5.404
Observations	918	918	918	918

Table XIV

Managers' Project's Idiosyncratic Risk Pricing - Futures Price

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1995 to 2010. The unit of observation in the underlying table is at the firm i , year t , and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). In this regression specification, the project's internal rate of return is estimated using the *36-month Bloomberg Natural Gas Futures* prices instead of the EIA three-year price forecast. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%) _{i,t,k}				
	(1)	(2)	(3)	(4)	(5)
(β_1) Projects' Average Idiosyncratic Risk _{i,t,k}	7.153*** [3.74]	7.149*** [3.75]	7.145*** [3.74]	7.304*** [4.24]	6.228*** [3.29]
(β_2) Budget _{i,t}	-0.003 [-0.52]		-0.006 [-0.80]		
(β_3) Assets _{i,t}		0.001 [0.12]	0.003 [0.48]		
(β_4) Average Natural Gas Production Level _{i,t,k}	0.736* [1.76]	0.736* [1.76]	0.737* [1.76]	0.763 [1.37]	0.728 [1.30]
Firm Fixed Effect _i	Yes	Yes	Yes	No	No
Year Fixed Effect _t	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect _{i,t}	No	No	No	Yes	Yes
Portfolio Fixed Effect _k	No	No	No	No	Yes
R-Squared	0.548	0.548	0.548	0.784	0.784
F-Statistic	6.504	5.021	5.332	8.985	5.404
Observations	3,416	3,416	3,416	3,416	3,416

Table XV**Managers' Project's Idiosyncratic Risk Pricing - EIA State's Wellhead Price**

This table reports coefficient estimates from an OLS regression for the effect of projects' idiosyncratic risk on firms' discount rate, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The time period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the firm i , year t , and portfolio k level. *Project's Average Idiosyncratic Risk* denotes the average projects' idiosyncratic risk measure for each firm-year portfolio (i.e., the high or low idiosyncratic risk portfolio). In this regression specification, the project's internal rate of return is estimated using the wellhead spot price specific to each state (Source: https://www.eia.gov/dnav/ng/ng_prod_whv_a_epg0_fwa_dpmsf_a.htm) instead of the EIA price forecast. The variable *Project's Average Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Discount Rate (%) _{i,t,k}				
	(1)	(2)	(3)	(4)	(5)
(β_1) Projects' Average Idiosyncratic Risk _{i,t,k}	7.162*** [3.32]	7.158*** [3.31]	7.166*** [3.29]	7.200*** [3.40]	6.410*** [2.76]
(β_2) Budget _{i,t}	0.007 [0.70]		0.008 [0.49]		
(β_3) Assets _{i,t}		0.002 [0.68]	-0.001 [-0.15]		
(β_4) Average Natural Gas Production Level _{i,t,k}	0.690* [1.82]	0.692* [1.83]	0.689* [1.84]	0.547* [1.67]	0.519 [1.56]
Firm Fixed Effect _i	Yes	Yes	Yes	No	No
Year Fixed Effect _t	Yes	Yes	Yes	No	No
Firm-Year Fixed Effect _{i,t}	No	No	No	Yes	Yes
Portfolio Fixed Effect _k	No	No	No	No	Yes
R-Squared	0.469	0.469	0.469	0.738	0.739
F-Statistic	6.512	5.117	6.083	7.701	4.737
Observations	3,946	3,946	3,946	3,946	3,946

Appendix Table I

Arp Model Estimation

This table reports coefficient estimates from an OLS regression, and t-statistics robust to heteroskedasticity and within-firm dependence in bracket. The period of the sample is from 1983 to 2010. The unit of observation in the underlying table is at the well j and well's age m (in month) level. Subscript p denotes specific township, and subscript t indicates the year well j was drilled. The Age variable corresponds to the well age m (in month) raise to the power of the superscript. For example, Age^2 denotes the well's age in month raised to the power of 2. The variable $Depth_j$ denotes the natural logarithm of the well's total vertical depth in foot. The variable $Local\ Information_j$ corresponds to the natural log of the number of wells drilled in well j 's township at the moment of drilling well j . The variable $Firm's\ Local\ Experience_j$ denotes the natural log of the total number of wells drilled by firm i in well j 's township, at the moment of drilling well j . $Firm\ Total\ Experience_j$ represent the natural log of the total number of wells drilled by firm i , at the time of drilling well j . The precision of those coefficient is important to properly match the realized production data. For this reason, I allow for 21 digits. See appendix B for a complete description of the model derivation. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Ln(Gas Well Monthly Production _{j,m})
(β_1) Age^1	-0.046123952293677099312230*** [-205.33]
(β_2) Age^2	0.000802229619753800043784*** [73.52]
(β_3) Age^3	-0.000011060405281200000582*** [-46.35]
(β_4) Age^4	0.000000095973699714300002*** [35.72]
(β_5) Age^5	-0.000000000484147915426000*** [-29.96]
(β_6) Age^6	0.00000000001290652064010*** [26.20]
(β_7) Age^7	-0.000000000000001402168849*** [-23.46]
(β_8) $Ramp_0$	-0.508063974623592096158120*** [-184.07]
(β_9) $Ramp_1$	0.032797358221284100832094*** [12.40]
(β_{10}) $Depth_j$	0.260683920294977111709045*** [189.55]
(β_{11}) $Local\ Information_j$	-0.004502789277263300089793*** [-4.53]
(β_{12}) $Firm\ Local\ Experience_j$	0.038126923544065098592437*** [31.90]
(β_{13}) $Firm\ Total\ Experience_j$	0.015990787856916301168386*** [38.76]
Firm-Year Fixed Effect _{i,t}	Yes
Township-Year Fixed Effect _{p,t}	Yes
R-Squared	0.686
Observations	30,420,544

Appendix Table III
Projects' Idiosyncratic Risk and Probability of Dry Hole

This table reports the incidence rate ratio estimates of a Poisson regression, and t-statistics robust to heteroskedasticity and within-township dependence in bracket. A coefficient value greater than 1 indicate a positive relation between the variable of interest and the outcome variable, while a value smaller than 1 indicate a negative relation. The unit of observation is at the township p , and year t level. The dependent variable, *Number of Dry Hole*, is a count variable that corresponds to the number of dry wells drilled in a given township-year. For example, a value of 2 indicates that there were 2 dry holes drilled in the township during that given year. *Project's Idiosyncratic Risk* $_{p,t}$ denotes the cross-sectional dispersion of the well's idiosyncratic productivity shock, computed at the township p and year t level. The variable *Project's Idiosyncratic Risk* is scaled by its standard deviation to simplify the lecture of the table and facilitate its comparison with the other regression tables. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Number of Dry Holes $_{p,t}$			
	(1)	(2)	(3)	(4)
(β_1) Project's Idiosyncratic Risk $_{p,t}$	1.476*** [9.56]	1.425*** [7.54]	1.377*** [2.66]	1.532*** [2.86]
(β_2) Township Average Production $_{p,t}$	0.999*** [-4.40]	0.999*** [-4.71]	0.999*** [-3.31]	0.999*** [-2.72]
Year Fixed Effect $_t$	No	Yes	No	Yes
Township Fixed Effect $_p$	No	No	Yes	Yes
Pseudo R-Squared	0.128	0.170	0.278	0.295
Observations	12,386	12,386	12,386	12,386

